

# Financial modeling of the Nordic forward market for electricity

*An Econometric Approach using time series*

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Thesis for the Degree  
Master of Economic Theory and Econometrics

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# Preface

The completion of this thesis marks the end of a five year program within the field of economics. It qualifies to the degree “*Master of economic theory and econometrics*”. I have faced both challenges and setbacks, but the experience as a whole has pushed me a great step forward.

My greatest acknowledgments go to my supervisor Professor Ragnar Nymoen at the department of economics, University of Oslo. He has supplied valuable advice and guidance from the beginning to the end. In fact it was during Ragnar’s computer class in “Econometrics – Modeling and systems estimation” autumn 2011 that I found the inspiration to undertake this thesis.

I would also like to thank Andres Bratterud for taking the time to proof read the thesis, his comments have been useful.

Data for my thesis has been made available by Pontus Ripstrand in NASDAQ OMX Commodities (Nord Pool), and Anika Kluge in the European Energy Exchange. This thesis would not exist without the possibility to analyze data compiled on their respective exchanges, and I thank them both for giving me access to it.

Finally I want to thank my colleagues in NASDAQ OMX Oslo ASA – The market surveillance department, for always being interested in a discussion on the electricity markets. It has been a great source of knowledge to me.

Any remaining inaccuracies and errors in this thesis is my own responsibility

May 2012,

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# Summary

In this thesis I have investigated a small part of the extensive Nordic electricity market. My intention was to model the forward Nordic “year contract” for 2010, and its dynamics in relation to a set of explanatory variables observed over three years. My goal was to derive interpretable and statistically significant results, allowing me to better understand the fundamentals in the above mentioned market.

The thesis is also an empirical and statistical investigation of certain truths regarding the relationship between variables in the Nordic electricity market. They are often referred to by market commentators and others who might have a say. An example of such a truth is the common assumption that the price of oil is a good indicator for the price of electricity. A notion I also find empirical evidence for in chapter six.

The findings presented in this thesis support most of the assumptions made in the above context, and can even suggest further explanation. However, they are based on data sets from a limited time period, which has to be taken into account.

The chapters are organized in the following manner; Chapter 2 is an introduction into the Nordic electricity market with a short summary of the most important aspects the reader needs to know to understand the following chapters. Chapter 3 presents the main hypothesis and assumptions regarding the variables included in the thesis and their function. It also holds demarcations and further specification of what is to be included in the thesis. Chapter 4.1-2 consists of the theoretical framework needed to understand how the estimation method has been conducted. 4.3-5 presents an exposition of the statistical tests and misspecification tests vital for statistical analysis. Lastly in 4.6, the use of the Autometrics algorithm has been accounted for. Chapter 5 presents the data sets that I have used, how they are denoted and what values they are measured in. Chapter 6.1-6 holds all the empirical results extracted from Models – 1 to 4, spanning from year 2007-2009. Chapter 7 is an extension of chapter 6, where I have used instrumental variables and two stage least squares to further investigate Model – 3 with observations from 2007. Chapter 8 concludes the thesis and suggests some interesting extensions for further investigation.

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# 1 Introduction

The Nordic electricity market had a turnover of 1204 TWH in 2010, which translates to roughly 61 277 million Euros<sup>1</sup>. It is the world's largest electricity exchange, and has been a pioneer in creating an exchange traded market for electricity since the start in 1996. Given the size of the market and its position as the most mature market, it is important for an economist working within this field to be able to understand and analyse the complex and ever changing dynamics of the electricity market.

There are mainly two approaches to undertake such an analysis, represented by the so called “top down” and the “bottom up” analysis. The latter is often based on microstructure analysis of the aggregated supply and demand for electricity in the short term. The main question is often, what happens to equilibrium if supply and/or demand changes? The former approach, which has been used in this thesis, is a top down analysis of the market in general. One can argue that it is a “macro” approach in analysis of the electricity market. We observe actual prices of several products over a given time horizon, and try to understand the intertwined relationship between them using a number of regression models.

Since its start in 1996 the Nordic market for electricity has changed substantially, in particular regarding size and scope. From being a joint Norwegian and Swedish operation it now consists of seven Nations, and still has potential to expand. The number of products listed on the exchange has also increased to meet new demand from market participants. This gives them an increased possibility to exploit the full spectre of advantages in a financial market. There are contracts for, day, week, month, quarter and year. In addition options in the form of puts and calls are listed. More exotic products like contracts for difference (cfd's) and other derivatives are also available.

In 2005 the Nordic electricity market and energy markets in general, underwent a major change. The European Union Emission Trading Scheme's first stage (out of three) was implemented, which effectively changed the fundamentals of the electricity markets. The goal is to reduce green house emissions by creating a pricing system for emissions - or pollution, in addition to fixing the total amount of emissions. The first phase lasted from 2005 to 31. December 2007 followed by phase two which will last until 31. December 2012.

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<sup>1</sup> Statistics from [www.nasdaqomxcommodities.com](http://www.nasdaqomxcommodities.com) «key figures»

This thesis has analysed times series data both from 2007 and 2008, and has come up with interesting results with respect to emissions in these periods. It will at least point out significant changes between the two years. As is commonly known, electricity generation does account for a substantial amount of emissions, in particular coal fired power plants. Subsequently, power producers must incorporate the cost of pollution into their aggregated cost function. Which imply that “emissions” in general will have a significant impact on the cost of producing electricity.

The German electricity market, being the largest in Europe, is also an important input into the Nordic electricity market. The main reason for this is that 1) there are international grid connectors between the Nordic region and Germany, both in Denmark and Sweden. Therefore the possibility to trade is present. And 2) because the Nordic and the German energy mix to some extent are similar to each other, the products are comparable.

As mentioned before, changes that have a fundamental impact on the composition of the electricity market happen from time to time. It may be preannounced like the EU ETS, or unannounced like the immediate shut down of eight nuclear reactors in Germany following the disaster in Fukushima. Lastly it could be unannounced and unattended like the financial crisis of 2008 and beyond. Therefore a time series analysis spanning over several years is needed to understand both the dynamics between variables, and the development over time. In the empirical sections below I will use the program PcGive 13 in OxMetrics and the Autometrics algorithm to analyze the statistical relationship over time.

The thesis has been organized in the following manner. Chapter two is an introductory discussion of the background and market structure of the Nordic electricity market. A short description of the symbiotic relationship between the so called physical and the financial market is also presented. This is to give the reader a chance to get a basic understanding of the uniqueness of electricity markets. Chapter three consists of the authors’ main hypothesis and assumptions about the dynamics of the market. In chapter four we go through the theoretical framework and specification of the econometric model used, it also holds details of statistical tests and technicalities, which is the backbone of the thesis. This is followed by a description of the data and datasets in chapter five. The empirical part is located in chapters six and seven and this is where the estimation results of Models 1 – 4 is presented. In chapter seven we experiment with two stage least squares estimation and instrument variables. Chapter eight concludes the thesis.

## 2 The Nordic electricity market

### 2.1 Background

The Norwegian electricity market was deregulated the 1<sup>th</sup> of January 1991 with the intent of harvesting efficiency gains from a free market and to maximize social welfare. The deregulation was based on the energy act of 29<sup>th</sup> of June 1990 or “Energiloven<sup>2</sup>” in Norwegian, which opened for liberalization of the Norwegian electricity market. In 1996 a joint market between Norway and Sweden was created. This was the first multinational electricity market in the world.<sup>3</sup> In the following years, Denmark and Finland joined the market, and today even the Baltic countries are a part of the “Nordic” electricity market.

The price of electricity “tomorrow” is calculated on a daily basis. This is done with the aid of a sophisticated but operational auctioning system. Aggregated supply and demand decides the equilibrium price for tomorrow. The result is the spot - or system price, and the market is commonly known as the spot or Elspot market. Forward and future prices of electricity are formed in the financial market based on various fluctuations of interdependent variables, shocks and noise. These two markets are dependent on each other, and are commonly referred to as the Nordic electricity market.

The financial market in general, has played an important role ever since the first stock exchange in Amsterdam of 1609. The financial market serves two important functions, both theoretically and empirically. The first is the time dimension where agents can use the market to desynchronize income and consumption, and thus smooth consumption over time. Secondly we have the risk dimension, where agents can reduce or eliminate risk at some cost.

“The market” shall in this thesis refer to the Nordic forward electricity market, as this is the platform where issues investigated in this thesis reveal themselves.

### 2.2 Market structure

The marketplace ‘Elspot’ is special in the sense that the product is actual electricity, which cannot be stored once produced - at least not in a large scale. To solve this problem,

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<sup>2</sup> <http://www.lovdato.no/all/nl-19900629-050.html>

<sup>3</sup> From [www.nasdaqomxcommodities.com](http://www.nasdaqomxcommodities.com) “our history”

electricity is traded simultaneously using a so-called implicit auction. The main outcome of the auction is the spot - or system price, which serves as a reference price the following day, excluding transmission constraints.

Within each country area prices are also calculated, Norway has five areas “NO1-5” Sweden has four “SE1-4”. Area prices reflect local prices when transmission capacity is taken into account.

Another important feature is that the direction of electricity will always flow to the area with the highest price. From a business point of view, one would want to sell to the highest bidder, so as to maximize income. Socially it is also optimal as high demand areas, or areas with the highest marginal willingness to pay, are given priority over low demand areas. High marginal willingness to pay translates into high marginal utility of consuming electricity. One can argue that the above process is in fact welfare maximization in the real world.

## **2.3 Price calculation – the day ahead market**

Electricity cannot be traded live in the same sense as equities, bonds and so on. This stems from the fact that producers as a whole cannot instantly supply more if demand suddenly spikes. Sometimes days of preparation is needed to increase production. However, the possibility to adjust production is available should the market be out of balance. This is handled in the “regulating market” and is often a consequence of sudden outages or slight miscalculations in the algorithm calculating tomorrow’s price. The solution to the above problems is the, in theory, simple process of deciding tomorrow’s price today. All agents producing or consuming electricity can submit offers to sell or bids to buy for the next day facing prices from -200 to 2000 Euro. For example an electricity producer owning a small power plant might submit the following bid; “If I can get a price of 20 EUR or more per MWH from 0700-0800 the 5<sup>th</sup> of May, I will supply 50 MWH in that period.” The algorithm would take the bid into account when calculating tomorrow’s price.

## **2.4 Risk in the financial electricity market**

The risk involved in the shifting prices of the physical market can be handled in the financial forward and future market. Agents in the financial market could agree on a future price and

volume of electricity today, and thus eliminating future uncertainty<sup>4</sup>. By doing this participants with less risk appetite can hedge their exposure, with the help of agents willing and able to take that risk on. Examples of agents might be a physical producer interested to “lock” a certain profit sometime in the future. The producer would have to sell a contract stating that he will supply the previously agreed-upon amount and price at that time in the future. For a transaction to take place there also has to be a buyer willing to pay the price presented in the market. This could for example be an investment bank taking advantage of a “mispriced” contract, buying on behalf of a client, or for some other reason buying what the physical producer is selling. There are limitless possibilities for participants to use the financial market for risk management, trading or hedging to mention some.

## **2.5 An important distinction between the financial and physical market**

As noted before, the day-ahead market and the financial electricity market coexist and are dependent on each other. Therefore we must distinguish between a contract with physical delivery, and one with financial delivery i.e. cash settled. This thesis has analyzed the financial market, and thus all contracts are cash settled. That is, there is no delivery of actual electricity, only cash. The only exception is in the market for European allowances, where a “document of confirmation” is obtainable. Financial contracts have similar names, and are denoted in the same way as “actual” contracts for electricity, so that a producer selling  $x$  MWH easily can hedge  $x$  MWH in the financial electricity market.

For example, if a producer wants to sell 100 MWH at time  $D$  and hedge or lock a price  $P$ , he would want to buy a contract where he agrees to sell 100 MWH at price  $P$  on date  $D$ . When date  $D$  has arrived, he would take the price  $\pi$  calculated by the day-ahead algorithm, and receive a cash settlement if  $\pi < P$ . He would receive nothing if  $\pi > P$ .

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<sup>4</sup> See Hull (2008) for a theoretical framework around the pricing of future and forward contracts

### 3 Market segmentation and variables

Within the financial market it is custom to distinguish between short and long term electricity contracts, referred to as “the front” and “the curve” by traders and market commentators. The very short term, i.e. the next day, week and month weather forecasts are the main price driver. This is a result of the mainly hydro electric Nordic energy market, where water are of major importance. For the long term we have “the curve” consisting of several quarters and year-products.

Contracts exist for all the above-mentioned periods. In essence they are agreements to buy or sell X megawatt per hour throughout that period. There is no physical delivery of electricity in the financial market, only cash settlement based on the difference between agreed and actual price - which is calculated by the day-ahead algorithm. Participants can choose to close their position before delivery, which would be equivalent to buying an item at price x and selling it at price y.

As a result of the inherent complexity of the weather system one cannot forecast the weather with a good accuracy several weeks, months and years ahead. Our best estimate is the seasonal weather forecast published by, amongst others, the Norwegian institute of metrology<sup>5</sup>, which calculates an estimate of the temperature for the next three months. The results are presented as deviation from a historic normal based on the average temperature from 1961 to 1991. The seasonal forecast does give an indication of what state the weather system will be in, but will not be as detailed as the forecast for tomorrow.

Despite the weather forecasts uncertainty and the dependency of the electricity market on the weather. Forward contracts with maturity up to 5 years in the future are traded daily on the electricity exchange. Prices of these derivatives vary on a daily basis, and they will be the object of econometric models that I present later. In the following sections I will present my hypothesis of what the main price drivers in the forward Nordic electricity market is, and give a short introduction of the variables utilized in econometric modeling.

To capture the price movements described below, a set of variables has been used. They are: Nordic and German Contracts of electricity, European allowances, certified emission reductions, natural gas and coal contracts. All these variables have in common that they are

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<sup>5</sup> See [http://met.no/Sesongvarsel%3A+mai-juli.b7C\\_w7LMYN.ips](http://met.no/Sesongvarsel%3A+mai-juli.b7C_w7LMYN.ips) for an example of a seasonal forecast

financial contracts traded daily on the exchange. They are to be delivered (financially) on a specific point in time in the future. In addition we have used the spot price of Brent Blend oil from 2007 to 2009. It is worth noting that all observations (time series data) are drawn from the same consecutive days, both the financial contracts and the spot price of oil.

I will now state my assumptions about how the market price of a contract is generated, in other words, how are traders and other market participants able to submit bids and asks on contracts of electricity delivered the next year?

In absence of reliable weather forecasts for the relevant time horizon, one must turn to other electricity generating systems for information. Outside the Nordic region, so called thermal generation is widely used. This includes nuclear, coal, gas and oil driven power plants that all have in common that their input factors is traded in a forward and spot market. Knowing these prices makes it possible to accurately forecast marginal cost of production, which is recognized as an indicator of future electricity prices.

The Nordic region does rely on thermal as well hydro powered generation. In Denmark coal is widely used as fuel in power generation. Sweden and Finland are dependent on nuclear power generation. I thus assume that the price of fuel will have an impact on the Nordic curve, mainly through the direct effect from the use of thermal generation within the Nordic region, and indirectly by trade with Germany and adjacent sources. Uranium, which is the main input factor in nuclear generation, will not be included in this thesis. The reason for this is that price data for uranium, and other related input factors was not available to me when preparing for this thesis. It is however worth noting that “Uranium is not traded in an open market” (Wikipedia<sup>1</sup>), deals are mainly done bilaterally between producer and consumer implying that official settlement prices may be hard to come by.

Uncertainty enters into the model through the continuously changing prices of fuel, and unexplained shocks. As a result it is natural to include several sources of fuel as explanatory variables. Coal, natural gas and oil are the most influential and must be included.

In the EU, about 30% of all electricity is generated by power plants that use coal as fuel. I assume that the price of coal will have a major effect on the cost function of power plants that utilize coal, which again will have an effect on their produce, namely electricity.

The market for coal is both regionally segmented and have other frictions that make it difficult to speak of “one price of coal”. On the other hand, the price of coal across regions tends to rise and fall with the price of oil, and this correlation can be utilized for estimation purposes. Specifically, in the econometric models that I report below I will use the price of North Sea “Brent” oil as a general representative for fossil fuels. I will also include both coal and natural gas in addition to oil, as to investigate the dynamics in my models when including more variables and hence more price information. The level of significance and joint explanatory power is of special interest.

The European Union Emissions Trading Scheme “EU ETS” was launched in 2005 and was the first large emissions trading scheme in the world. The goal is to combat climate change by creating a market for emissions, which is a major pillar of EU climate policy (Wikipedia2). As a result, thermal power producers, in particular power plants using coal as an input factor, have to buy quotas in the market if they want to increase emissions beyond their government and EU determined hand outs. In other words, costs increase which leads to a price increase in the final product. I assume that the price of emissions influences the price of electricity. A rising price of emission rights should generally lead to higher costs when producing electricity. I will use European emission allowances in my analysis, this will allow me to better understand how politics around climate change affects the price of electricity.

I also assume that German Year-contracts have explanatory power on Nordic Year -contracts. First of all, the Nordic market is physically connected to the German market, which in itself represents a factor that will equalize prizes. The German contract also exhibits certain similarities to the Nordic contract. They both have elements of thermal and nuclear generation in them, and therefore they are comparable on the cost side. I assume that a change in one of the contracts will be translated onto the other, and would further speculate that the German market is leader and the Nordic is follower, this based on market size. But a priori it is not possible to say anything about the strength of the effect, so empirical estimation is required.

Power generation in the Nordic region is dominated by hydroelectric and nuclear generation, which only partially resembles the German situation. Regardless, I expect to see the German contract have some explanatory power on the Nordic contract. In fact, Germany has the largest electricity market in Europe, and that alone should turn it into a leading market, with explanatory power across regions.



Regarding the flow of electricity I assume that the net flow of electricity goes from the Nordic region to Germany. The low marginal cost of hydroelectric production versus the higher marginal cost of thermal generation with carbon included, should result in an export of electricity to Germany and an import of higher prices into the Nordic region.

Natural gas contracts should exhibit some explanatory power on the price of electricity, but to what extent I am uncertain. The marginal cost of a power plant using natural gas as input factor is higher than that of a plant using coal. In effect this leads to a situation where natural gas-fueled plants only come into operation when the price of electricity is high or the so called “peak load hours”. None the less, natural gas is a vital part of the thermal “mix” and I expect to see some explanatory power when modeling the electricity market.

I assume that past prices can explain future prices. One might suspect that day to day price - changes follow some form of distribution, for example lognormal and mean reverting. There might also be some form of momentum in the sense that positive days are followed by negative and so on. Given enough data, one might find a certain pattern that may be of use when trying to understand the forward price of electricity.

Renewable sources of electricity, for example from the sun and wind, will not be included in this thesis. This is despite the increasing importance of such. It would be both interesting and useful to include renewables in my analysis, but it is outside the scope of this thesis which is concerned with fuels and the forward market.

The “weather factor” would be a natural extension, and I assume that the same econometric - and statistic tools could be applied. However, embarking on an analysis of the “weather factor” and or the renewable market would demand much research and time, and is probably best left out at this point.

Other factors like; freight prices, expected consumption and production, transmission capacity, the political situation, foreign exchange rate, economic growth and the macroeconomic situation could in principle have an impact, but to what extent is uncertain. Therefore, I will not include these variables in this thesis.

Given the above distinction and specifications, I will in the empirical sections below consider and assess all factors with the use of econometric models.

## 4 Vector Autoregressive specification and econometric models

To formalize the hypotheses above I will give a mathematical representation in terms of a system of equations. In the following I will use observations from 2009 as an example, but observations from both 2008 and 2007 have been utilized in econometric modeling. The representation is identical for 2008 and 2007.

The variables for 2009 are as follows:  $Y_{1,t}$  is end of day observations from 2009 of the Nordic contract for electricity delivered in January 2010, the contract is denoted in Euros.  $Y_{2,t}$  is end of day observations from 2009 of Brent North Sea oil, denoted in US dollars.  $Y_{3,t}$  and  $Y_{4,t}$  are end of day observations from 2009 of European allowances and Certified emission reductions, or in other words the right to pollute.  $Y_{3,t}$  and  $Y_{4,t}$  is denoted in Euros.  $Y_{5,t}$  are end of day observations from 2009 of European allowances traded on another platform as the previous mentioned “EUA”, it is denoted in Euros.  $Y_{6,t}$  is end of day observations through 2009 of the German base load contract for electricity delivered in January 2010.  $Y_{7,t}$  and  $Y_{8,t}$  are Contracts for delivery of coal and Natural gas delivered in January 2010, Coal is denoted in US Dollars and Natural gas is denoted in Euros.

### 4.1 The VAR

Although the hypothesis formulated above have  $Y_{1,t}$ , the Nordic year-contract, as the dependent variable, and the seven other variables as explanatory variables, it is useful to think of the full set of variables as jointly determined in a system of dynamic equations, and to derive econometric models from the system that can be used for testing the hypothesis.

To clarify this point I first represent the variables in a Vector Autoregressive “VAR” system and then show that a conditional econometric model for the Nordic year-contract can be derived from the VAR.

If we assume that  $Y_{1,t}$  and  $Y_{k,t}$  are stochastic variables generated by the following system of linear equations

$$\begin{array}{rcl} Y_{1,t} & = & \mu_{Y_{1,t}} + \varepsilon_{1,t} \\ \vdots & & \vdots \\ Y_{k,t} & = & \mu_{Y_{k,t}} + \varepsilon_{k,t} \end{array}$$

In the above system  $k = 8$ , but for presentation purposes and without loss of generality we can set  $k = 2$ .

It follows that  $\varepsilon_{1,t}$  and  $\varepsilon_{2,t}$  has a joint probability distribution, for example:

$$\begin{pmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \end{pmatrix} \sim N \left( \mathbf{0}, \begin{pmatrix} \sigma_{Y_{1,t}}^2 & \omega_{Y_{2,t}Y_{1,t}} \\ \omega_{Y_{1,t}Y_{2,t}} & \sigma_{Y_{2,t}}^2 \end{pmatrix} \right)$$

$\varepsilon_{1,t}$  and  $\varepsilon_{k,t}$  are bivariate normal with expectation zero and covariance matrix:

$$\begin{pmatrix} \sigma_{Y_{1,t}}^2 & \omega_{Y_{2,t}Y_{1,t}} \\ \omega_{Y_{1,t}Y_{2,t}} & \sigma_{Y_{2,t}}^2 \end{pmatrix}$$

Where  $\sigma_{Y_{1,t}}^2$  is the variance of  $Y_{1,t}$  and  $\omega_{Y_{1,t}Y_{2,t}}$  is the covariance between  $Y_{1,t}$  and  $Y_{2,t}$

The correlation coefficient between  $\varepsilon_{1,t}$  and  $\varepsilon_{k,t}$  is:

$$\rho_{Y_{1,t}Y_{2,t}} = \frac{\omega_{Y_{1,t}Y_{2,t}}}{\sigma_{Y_{1,t}}\sigma_{Y_{2,t}}}$$

If we let  $\mu_{Y_{1,t-1}}$  and  $\mu_{Y_{2,t-1}}$  denote the expectations of  $Y_{1,t}$  and  $Y_{2,t}$  conditional on the prehistory, we can see that

$$\mu_{Y_{1,t-1}} = E[Y_{1,t} | Y_{1,t-1}, Y_{2,t-1}] = \alpha_{1,1}Y_{1,t-1} + \alpha_{1,2}Y_{2,t-1}$$

$$\mu_{Y_{2,t-1}} = E[Y_{2,t} | Y_{2,t-1}, Y_{1,t-1}] = \alpha_{2,1}Y_{2,t-1} + \alpha_{2,2}Y_{1,t-1}$$

The specification of the above model starts with the following VAR

$$\begin{pmatrix} Y_{1,t} \\ Y_{2,t} \end{pmatrix} = \begin{pmatrix} \alpha_{1,1} & \alpha_{1,2} \\ \alpha_{2,1} & \alpha_{2,2} \end{pmatrix} \begin{pmatrix} Y_{1,t-1} & Y_{2,t-1} \\ Y_{1,t-2} & Y_{2,t-2} \end{pmatrix} + \begin{pmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \end{pmatrix}$$

## 4.2 The conditional model

It follows that the conditional model for  $Y_{1,t}$  given  $Y_{2,t}$  is:

$$Y_{1,t} = \beta_{1,1}Y_{1,t-1} + \beta_{2,1}Y_{2,t} + \beta_{2,2}Y_{2,t-1} + \varepsilon_t \quad (1)$$

Which can be estimated by ordinary least squares “OLS” Subsequently we have:

$$\beta_{1,1} = \alpha_{1,1} - \frac{\omega_{Y_{2,t}Y_{1,t}}}{\sigma_{Y_{2,t}}^2} \alpha_{2,1}$$

$$\beta_{2,1} = \frac{\omega_{Y_{2,t}Y_{1,t}}}{\sigma_{Y_{2,t}}^2}$$

$$\beta_{2,2} = \alpha_{1,2} - \frac{\omega_{Y_{2,t}Y_{1,t}}}{\sigma_{Y_{2,t}}^2} \alpha_{2,2}$$

In addition we have

$$E[\varepsilon_{1,t} | Y_{1,t-1}, Y_{2,t}, Y_{2,t-1}] = 0$$

$$\text{Var}[\varepsilon_{1,t} | Y_{1,t-1}, Y_{2,t}, Y_{2,t-1}] \equiv \sigma^2 = \sigma_{Y_{1,t}}^2 (1 - \rho_{Y_{1,t}Y_{2,t}}^2)$$

Lastly

$$Y_{2,t} = \alpha_{2,1}Y_{1,t-1} + \alpha_{2,2}Y_{2,t-1} + \varepsilon_{2,t} \quad (2)$$

$$\text{Cov}(\varepsilon_{1,t} | \varepsilon_{2,t}) = 0$$

As before, i.e. the marginal model for  $Y_2$  is the same as the second line of the bivariate VAR above. Together with the conditional model (1) for  $Y_1$  given  $Y_2$ , the marginal model gives a “one-to-one” re-parameterization of the VAR.

The point of working with the conditional model (1) is that we can then investigate the conditional predictability of the “year 2010” contract without having to model the whole system in “one go”. Specifically, the hypothesis that the year 2010 contract does not depend on  $Y_{2,t}$  “today” can be tested with statistical t-test on the parameter  $\beta_{2,1}$ . Moreover, the joint hypothesis that the year 2010 contract is uncorrelated with  $Y_{2,t}$  both contemporaneously and lagged can be tested with a F-test for the joint hypothesis  $\beta_{2,1} = \beta_{2,2} = 0$

However, since we use high frequency (daily) time series data, the validity of statistical t- and F-tests cannot be taken for granted. Therefore the next chapter discusses some important methodological issues on times series econometrics, and explains how I have attempted to tackle them in my analysis.

If the conditional analysis gives interpretable results, a more complete analysis with system methods can be undertaken. This can be done with so called recursive models, simultaneous equation models, or even a combination of the two.

## 4.3 Statistical tests

Statistical tests are very important in econometrics, they give the econometrician the ability to statistically check various hypotheses about the data at hand. The single variable test, “t-test”, and the joint significance test, “F-test”, are cornerstones in parameter testing, and beyond.

They are discussed in detail below.

### 4.3.1 t-test

The function of the t-test is to test a hypothesis about a single parameter. As an illustration we use an example based on the reduced form simplified equation described above. We want to check if  $\beta_{2,1}$  “the spot price of Brent oil” can explain variation in our endogenous variable  $Y_{1,t}$ .

$$Y_{1,t} = \beta_{1,1}Y_{1,t-1} + \beta_{2,1}Y_{2,t} + \beta_{2,2}Y_{2,t-1} + \varepsilon_t \quad (3)$$

We assume that the classical assumptions holds for the disturbance of the conditional model, but this assumption is automatically fulfilled if (3) is derived from the VAR with normally distributed disturbances.

We can now go forth and formulate a null hypothesis:

$$H_0: \beta_{2,1} = 0 \text{ versus } H_1: \beta_{2,1} \neq 0$$

To complete our analysis we need to define the t statistic or the t ratio of  $\beta_{2,1}$  which is defined as

$$t_{\widehat{\beta}_{2,1}} \equiv \widehat{\beta}_{2,1} / se(\widehat{\beta}_{2,1})$$

Together this constitutes that after all other variables has ben accounted for, the price of oil has no “effect” on the Nordic forward contract of electricity for the year 2010. In other words, we want to look at the variables effect ceteris paribus.

A critical value “c” is obtained by choosing a suitable significance level, which should be done in advance. This could for example be 5%, meaning that we accept a 5% probability of rejecting  $H_0$  when the hypothesis it is actually true. Lastly we need to state the degrees of freedom, defined by  $n - k - 1$ .

For the one sided test, the rejection rule states that  $H_0$  is rejected in favour of  $H_1$  at the 95% significance level if

$$t_{\widehat{\beta}_{2,1}} > c.$$

The significance level is defined as the probability of rejecting  $H_0$  when it is true. Therefore the significance level is conventionally set to a low level.

In this thesis we expect that a two sided test is relevant. We might want to test whether a lagged variable has a ceteris paribus effect on the explained variable, and that effect might be positive, negative or zero. The new rejection rule states that  $H_0$  is rejected in favour of  $H_1$  at the 5% significance level if

$$|t_{\widehat{\beta}_{2,1}}| > c.$$

It should be noted that there are various applications of the t-test, a test can be preformed to check if  $\beta_{2,1} = 0$  or  $\beta_{2,1} = \beta_{2,2}$  to mention some.

Another result worth mentioning is the “p-value” which generally states, what is the smallest significance level at which the null hypothesis would be rejected? “P-value” is often referred to when analysing the significance of variables.

### 4.3.2 F-test

The F-test is used when testing multiple hypothesis tests or joint hypothesis tests. Again using equation (1) we might be interested to investigate if  $\beta_{2,1}$  and  $\beta_{2,2}$  exhibits joint significance on our endogenous variable. The null hypothesis states:

$$H_0: \beta_{2,1} = 0 \text{ and } \beta_{2,2} = 0 \text{ versus } H_1: H_0 \text{ is not true}$$

The null constitutes two exclusion restrictions. To test this hypothesis we need to formulate an F-test using the sum of squared residuals “SSR” from the unrestricted model, which is the model with all variables included, and the “SSR” from the restricted model, where the excluded variables are not included. The F-statistic or F-ratio is formally represented by:

$$F \equiv \frac{(SSR_r - SSR_u)/q}{SSR_u/(n-k-1)}$$

Where  $SSR_u$  is the sum of squares from the unrestricted model,  $SSR_r$  is the sum of squares from the restricted model. “q” is the numerator degrees of freedom “df” where df = number of observations – number of estimated parameters. n - k - 1 is the denominator degrees of freedom.

F is distributed as an random variable with (q, n - k - 1) degrees of freedom, or formally;

$$F \sim F_{q,n-k-1}$$

We reject  $H_0$  in favour of  $H_1$  if  $F > c$ , where c is a predetermined and self chosen critical level.

As a final remark I wish to point out that in the following section on misspecification, the F-test is of great importance. Two points come to mind, direct use, for example to test auxiliary regressions, or it may be indirectly used in “rewritten form” but with a new name.

## 4.4 Misspecification tests<sup>6</sup>

As already noted, the t and F tests above are only valid when the regression model's disturbances have (near) classical properties, in particular there should be no autocorrelation<sup>7</sup>. In this section we will take a closer look on the main issues one might come across when investigating the statistical properties of the econometric model.

### Autocorrelation

Autocorrelation violates the classical assumption that the error terms are uncorrelated. It does not lead to biased estimators, but standard errors can be underreported and hence give a false impression of the t-statics. Absence of autocorrelation can be tested with the aid of the OLS residuals, and is an important part of misspecification testing of an estimated model. See Kennedy (2009) chapter 8 for a detailed discussion on autocorrelation.

As mentioned earlier the notion of no autocorrelation is important. The classical assumption states:

Conditional on the explanatory variable vector “ $\mathbf{X}$ ”, the errors in two different time periods are uncorrelated:  $\text{corr}(\varepsilon_t, \varepsilon_s | \mathbf{X}) = 0$ . To simplify the notation we abstract the conditioning and write this assumption more simply as  $\text{Corr}(\varepsilon_t, \varepsilon_s) = 0$ .

When autocorrelation is present, we will typically have  $\text{Corr}(\varepsilon_t, \varepsilon_s) \neq 0$ . To illustrate we use a very simplified version of the model above, where the Nordic forward contract is explained by the spot price of oil.

$$Y_{1,t} = \beta_{2,t} Y_{2,t} + \varepsilon_t \quad (4)$$

In addition we need a model for the disturbance, given by:

$$\varepsilon_{t,1} = \rho \varepsilon_{1,t-1} + \varepsilon'_t \quad \text{where } |\rho| < 1$$

and

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<sup>6</sup> Innføring I økonometri Bårdsen og Nymoen (2011, Chapter 8). In the empirical sections below I will use the program PcGive 13 in OxMetrics. See Doornik and Hendry (2009), and the misspecification tests as they are implemented in PcGive 13.

<sup>7</sup> Autocorrelation is often referred to as serial correlation



$$E(\varepsilon_t) = 0 \quad \text{Var}(\varepsilon_t) = \sigma^2 \quad \text{Cov}(\varepsilon_t, \varepsilon_{1,t-1}) = 0, \forall j.$$

$\varepsilon_{t,1}$  is an AR(1) process, or “auto regressive process of order one”. If  $\rho = 0$ , ordinary least squares gives estimators that are best linear unbiased estimators, or “BLUE”. If however,  $0 < \rho < 1$  we have positive autocorrelation and if  $-1 < \rho < 0$  we have negative autocorrelation

A consequence of autocorrelation is that the “default” OLS based variances for the parameter estimators are wrong. And this will undermine the t-statistic, and the corresponding p-values.

OxMetrics will by default test for serial correlation via the AR 1-2 test and report test statistics. This is simply an extension of the AR(1) test above which includes higher order disturbances. When using high frequency data, higher order correlation beyond the second degree can be of interest. In a model with 10 lags, AR1-10 test might be a suitable parameter.

To give a formal representation of the AR test we use an auxiliary regression, again using the same notation as above:

$$\varepsilon_{t,1} = \rho_1 \varepsilon_{1,t-1} + \rho_2 \varepsilon_{2,t-2} + \varepsilon_t \quad \text{where } |\rho_2| < 1 \text{ and } |\rho_1| < 1$$

The null hypothesis is as follows:

$$H_0: \rho_1 = \rho_2 = 0 \text{ versus } H_1: H_0 \text{ is not true}$$

The above null can be tested with a self chosen level of significance. Several researchers have contributed to this test for autocorrelation. See Godfrey (1978) and Harvey (1981) page 173.

## Normality and Jarque-Bera test

“The normality assumption on disturbances is important for the exact statistical distribution of OLS estimators and the associated test statistics”.

A formal test for normality can be constructed using expectation and variance, which is the first and second moment. Higher order moments can also be incorporated. Skewness, the third moment, is a measure of the symmetry of a probability distribution of a random variable. The fourth moment, Kurtosis, is the “peakedness” of the normal distribution. Therefore these numbers can give us a measure of how much of the probability mass that is located in the tails of the distribution.

The so called Jarque-Bera test for normality is automatically calculated in OxMetrics. It is a goodness of fit to the normal distribution - test based on skewness and kurtosis. The null hypothesis would be that there is no deviation from the normal distribution both in the form of kurtosis and skewness. See Jarque and Bera (1980).

One can also graphically inspect a histogram of the disturbance, and by that get a visual impression of how good a fit to Normal(0,1) the disturbance is.

### **Heteroscedasticity and “the White test”**

Heteroskedasticity is a situation where variance of disturbances is not constant over time. It does not cause OLS estimators to be biased, but can lead to a biased estimate of variances and standard errors. In other words, estimators do not capture the true variance of OLS. This can lead to issues with regard to hypothesis testing, for example t-tests.

The classical assumption on homoscedasticity states that:

Conditional on  $\mathbf{X}$ , the variance of  $\varepsilon_t$  is the same for all  $t$ :  $\text{Var}(\varepsilon_t|\mathbf{X}) = \text{var}(\varepsilon_t) = \sigma^2$ ,

$t = 1, 2, \dots, n$ .

Usually an F-test or White’s test for heteroscedasticity is applied when testing for heteroscedasticity. See for example White (1980) for a discussion on the matter.

A simplified version of White’s tests for heteroscedasticity is constructed using an auxiliary regression. Using the same notation as before.

$$\hat{\varepsilon}_{t,1}^2 = \beta_0 + \beta_1 Y_{2,t} + \beta_2 Y_{2,t}^2$$

We must have that the coefficients  $\beta_1$  and  $\beta_2$  are both zero for there to be homoscedastic disturbances. The null hypothesis is presented as:

$$H_0: \beta_1 = \beta_2 = 0 \text{ versus } H_1: H_0 \text{ is not true}$$

Where the above null can be tested as an F-test.

OxMetrics will, as in the case with autocorrelation, automatically test for heteroscedasticity and report the result with the correct amount of restrictions and degrees of freedom.

Again a visual inspection can be implemented. Data points of actual and fitted observations visualized in a histogram should **not** “fan out” as time passes. The second figure in “figure 8” on page 44 is a good example of absence of heteroskedasticity.

## ARCH test

Auto Regressive Conditional Heteroskedasticity is often found in time series estimation. It is a situation where the variance of the disturbance varies over time. It is also referred to as “time-varying volatility clustering”, which is periods of high volatility followed by low volatility, or a random order of such.

Again we use an auxiliary regression to test if

$$\text{Var}(\varepsilon_t | \varepsilon_{t-1}) = a_0 + a_1 \varepsilon_{t-1}^2$$

We can test the hypothesis of constant variance by the following auxiliary regression

$$\widehat{\varepsilon}_t^2 = a_0 + a_1 \widehat{\varepsilon}_{t-1}^2 \quad (t = 1, 2, \dots, T)$$

Our null hypothesis is:

$$H_0: a_1 = 0 \text{ versus } H_1: H_0 \text{ is not true}$$

OxMetrics will test for auto regressive conditional heteroskedasticity and report the results under the “ARCH test” statics.

## RESET<sup>23</sup> Test<sup>8</sup>

The RESET test is a test “whether non-linear combinations of the fitted values help explain the response variable. The intuition behind the test is that if non-linear combinations of the explanatory variables have any power in explaining the response variable, the model is misspecified<sup>9</sup>”

Linearity of parameters is an important assumption in classical regression analysis. The assumption often holds when using experimental data (data from a known data generating

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<sup>8</sup> See Greene (2011), p 177 for a discussion around the constructiveness of the RESET test

<sup>9</sup> Quote from Wikipedia “Ramsey RESET Test”

process), but might not or only partially hold when using real world data like Time Series observations.

Issues with non linear parameters can be addressed by linear transformations, this however might not be necessary. We could ignore the fact that there might be a measuring error, and rather investigate the impact it has on our conclusions. Because any non linear function  $Y_t = f(X_t)$  can be represented by a polynomial, we could test if our regression model excludes such a polynomial. The “regression equation specification error test” or RESET test, uses an auxiliary regression on the OLS estimators to investigate the correlation coefficient between a variable and the same variable squared, cubed and so on. We formulate an (simplified) auxiliary regression:

$$Y_{1,t} = \beta_2 \hat{Y}_{1,t}^2 + \beta_3 \hat{Y}_{1,t}^3 + \varepsilon_t$$

With the null and alternative hypothesis:

$$H_0: \beta_2 = \beta_3 = 0 \text{ versus } H_1: H_0 \text{ is not true}$$

Because of the joint null hypothesis, an F-test is applicable.

## 4.5 General to specific modeling using Autometrics

In this thesis, the conditional models that we need to specify and estimate will be much more complex than (1). First we have for the sake of exposition, abstracted for 8 of the explanatory variables that we introduced in chapter 3. Moreover, because we use daily data it is impossible to say a priori what a realistic dynamic specification of the conditional model with 8 explanatory variables might look like.

In the empirical section below I am going to rely on an automated algorithm for automatic general to specific modelling which is a part of the OxMetrics programme. The algorithm is called Autometrics. The following sub-section gives a brief description of the main features and properties of the algorithm.

## 4.6 Autometrics

Autometrics is a tool in the general to specific “GETS” framework developed by David Hendry and Hans-Martin Krolzig. As the name suggest, it is an automated algorithm that find the best simplified model of a general unrestricted model “GUM” that has been estimated on a given dataset. It can be especially helpful when estimating multivariate models with long and unspecified lag lengths. The model on page 11 is an example of this.

### 4.6.1 Main aspects

There are five main elements in the algorithm, the general unrestricted model, multiple path search, encompassing test, diagnostic testing and tiebreaker. It also holds extensions by Hendry and Krolzig in pre-search, multiple path search and iteration. “The aim of Autometrics is to improve computational efficiency, for example by avoiding repeated estimation of the same model”. The following short description is taken from Doornik, J.A. (2009).

- Pre-search.

The motivation to include a pre-search is the need to reduce computational effort and the empirical size. It handles the correlation between sets of variables and once a variable has been removed, it cannot reappear.

- The general unrestricted model “GUM”

The GUM is the starting point and provides the initial information set. A set of diagnostics ensures that the model is relevant and statistically well behaved. It should exhibit monotonicity (generally if  $x \leq y$  then  $f(x) \leq f(y)$ ) and also local sufficiency

- Multiple path search

An insignificant variable defines a reduction path. The algorithm will remove the variable with the lowest absolute t-value and re estimate the model. This process is repeated until all variables are significant. The same method can be applied to blocks of regressors and is called bunching. Removal of an entire block is the process of chopping.

- Encompassing test

The reduced model need to encompass the GUM and this is tested by a simple F-test of the removed variables, where the variable is kept in the model despite being insignificant. The procedure is repeated for every insignificant variable. Ideally we want to limit the loss of information relative to the GUM. The encompassing test is often refereed to as back-testing with respect to the GUM

- Other diagnostic tests

The current rejection, that is our model after variable(s) has ben removed, is subjected to a series of other tests. If one of the tests fails, the current rejection is rejected. Test for normality, residual correlation, residual ARCH and a chow test are applied.

- Tiebreaker

Personal preferences will count when choosing a model, however, an automated set of rules is adopted in Autometrics. The two main criteria are “the best fitting terminal model” and the “minimum Schwartz Criterion” also known as “Bayesian information criterion”.<sup>10</sup>

- Tree search as opposed to multiple path search

If we have a model with four variables, a tree search would start off with removal of the most insignificant variable followed by a re-estimation of the model using the tree variables that is left. The process would be repeated until one variable remains. The situation described above represents one out of four branches in the tree. In the second branch, the first variable removed in round one, would not be removed in the first elimination process.

- Pruning

Pruning is the notion of removing an entire branch, if at some node ‘back-testing with respect to the GUM’ fails. That is, if the model fails after removal of a variable, the remains of that branch will not be investigated. The process is governed by the main

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<sup>10</sup> See “J. K. Ghosh, M. Delampady, and T. Samanta (2006)” for a formal definition of the Bayesian information criterion

Autometrics p-value. It determines the lowest level of significance that a variable can have and still not be removed.

- Bunching

Bunching is as previously mentioned, the process of removing more than one variable at the time. Variables are tried on individual insignificance, bunched together and removed, followed by an F-test to check if we can remove them. If we fail to delete, the algorithm backtracks until a bunch can be deleted.

- Chopping

Chopping is the permanent removal of highly insignificant variables or a bunch of variables from the model.

- Performance of the algorithm.

When evaluating the performance of the algorithm two elements are important. Gauge which is a measure of the fraction of irrelevant variables in the final model, and potency which records the fraction of relevant variables that are in the model. These numbers are generated by repeated sampling - or Monte Carlo simulations. Using Gauge as an example and depending on how strict settings one chooses, we can assume that after repeated sampling, we have  $x$  irrelevant variables in the final model. In essence we answer the question: how valid are the variables included in the final model?

## 5 Data

The data used in this thesis are end of day observations of several different products. The data set has been organized as time series data, and all variables have been transformed to natural logarithms so that the effect of outliers is somewhat down weighted. All data are measured by the end of day closing price of the particular variable in a particular year (here 2007, 2008 and 2009 have been used). As a practical note, we wish to make the reader aware that “.” is used as decimal separator in this thesis. For example, 1.200 is **not** twelve hundred, but one point two.

The main product of interest is the Nordic year contract, denoted NOYR10. It is the natural logarithm of this variable, denoted LNOYR10 that will be the main endogenous variable we want to explain by econometric models. There are at all times available contracts for the next five years. In essence these are financial agreements to produce or consume one megawatt every hour in the particular year covered by the contract. The price is determined in the market. The contract is specified in a way that allows easy translation and relation to the physical market. In other words, a contract with actual delivery of electricity has the same specifications i.e. same time horizon, and is measured in the same units, as a contract with cash settlement.

The currencies involved are Euro and US Dollar. I have chosen not to convert dollars into Euros because foreign exchange rates in the period at hand have fluctuated considerably, and therefore represent a source of “noise” in the model.<sup>11</sup>

In the following discussion the variable “X” represent the year in which the instrument has been traded or observed. It can be 2007, 2008 or 2009. Different models use different years, therefore when giving a formal and general presentation the variable X has been used. Observations within the years are daily, or- end of day settlement prices.

The price of oil represented by “BRENTSPOT\_X” This is the end of day spot price of North Sea “Brent” oil, one of the leading price indicators of oil. We have spot prices ranging from 2007 to 2009. Main consumers are the European market.

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<sup>11</sup> However, the EURO/DOLLAR exchange rate is an interesting branch to investigate. See for example “Is Crude Oil Price Affected by the US Dollar Exchange Rate? By Alex YiHuang and Yi-Heng Tseng, Yuan Ze University, Taiwan. <http://www.eurojournals.com/finance.htm>



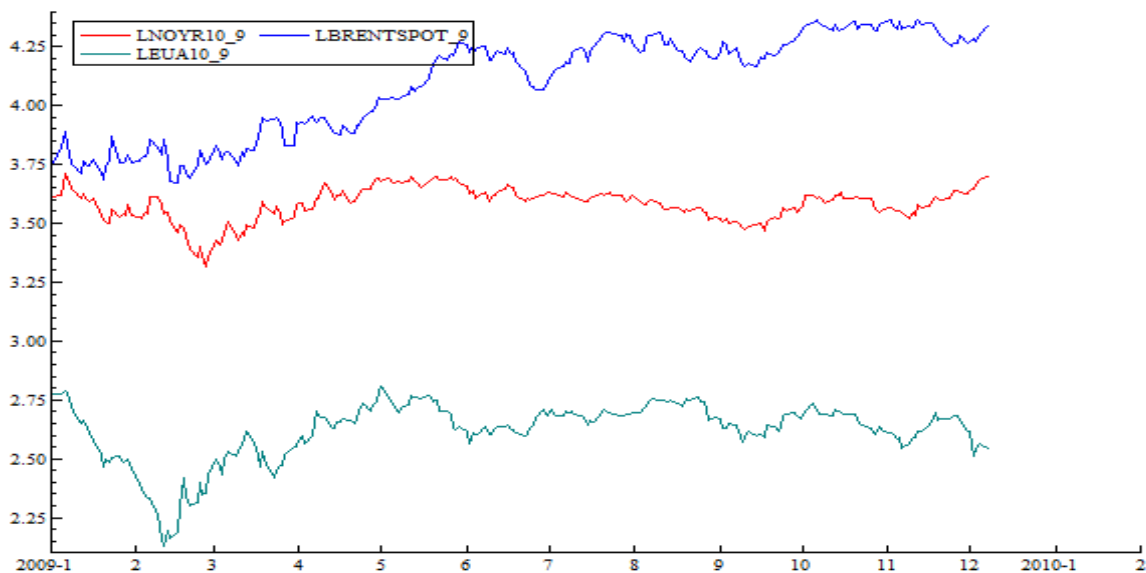
European allowances “EUADEC10\_X” in end of day observations. One lot - or contract, is 1000 ton of  $CO_2$ . The same applies for “EUAEX10\_X” which the same product traded on a competing exchange. Observations are end of day data within year “X”

Certified Emissions Reductions “CERDEC10\_X” are, as the name implies, an instrument that public or private entities can use to comply with the European allowance scheme, which in essence makes it yet another “price on emission”. They can be bought directly from the party making the reduction, or in a second hand market. They differ from EUA’s as they are payments to another agent for him to reduce his emissions.

The German base load contract “DEBL10\_X” is an agreement to buy or sell 1 MWH all hours in the year specified by the contract. Observations are end of day data within year “X”.

The following chart represents the development of NOYR10, EUADEC10 and BRENTSPOT\_9 all trading days in 2009. All variables have been transformed to logarithmic scale, which is denoted by a prefix “L” for each variable.

Figure 1. The Nordic contract (LNOYR10\_9), European allowances (LEUADEC10\_9), and the spot price of Brent Blend, year 2009 (LBRENTSPOT\_9). Logarithmic scale



Coal contracts<sup>12</sup> traded in for example 2009, where one contract is delivery of one ton of coal in January 2010. One contract can also consist of 1000 ton of coal. Observations are end of

<sup>12</sup> For specific details around delivery and settlement of coal and gas futures, see [www.eex.com](http://www.eex.com)

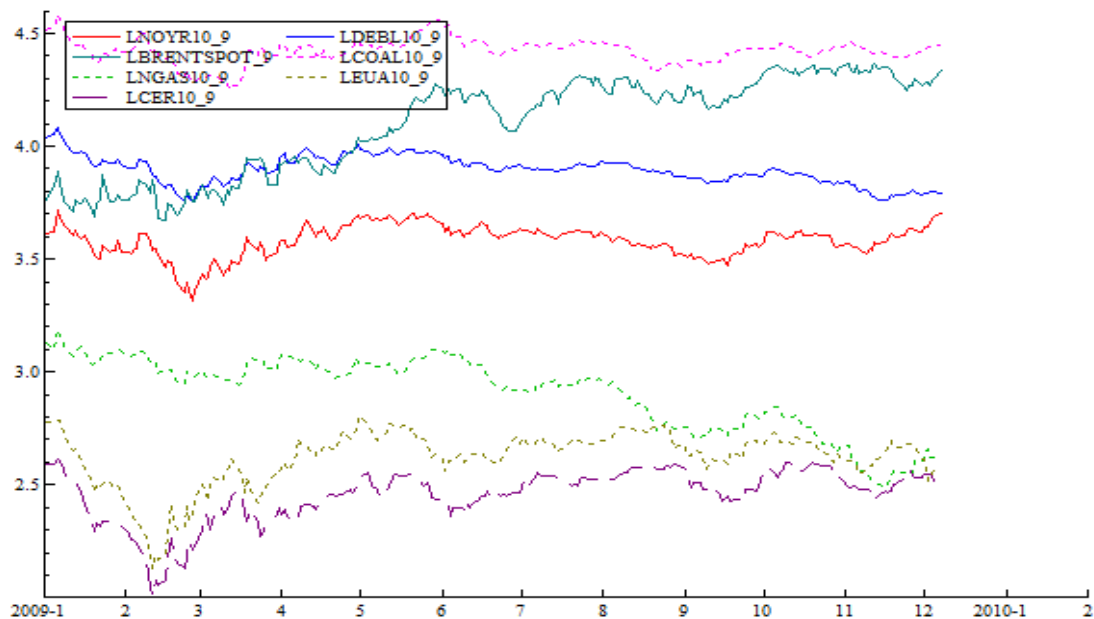
day settlement prices and the segment we have focused on is delivery in Amsterdam, Rotterdam and Antwerp “ARA”. Coal prices are denoted in US Dollars.

Natural Gas contracts are similar to coal contracts. The final product is electricity, and hence what is of interest is how many MWH one can produce using a certain amount of natural gas as input factor. Therefore buying a year-contract of natural gas would imply that one can produce 8760 MWH of electricity, which is one MW per hour all hours in one year.<sup>13</sup> Observations are end of day data within year “X”. Natural gas is denoted in Euros

The most important aspect regarding all contracts in my model is how a price change in one or more contracts related to the Nordic forward price of electricity. In that respect the value of change and the final result is of interest. Therefore I will not get into details on settlement and delivery and the surrounding process.

The following graph depicts all variables in the same diagram. The extent of explanatory power across variables will be investigated.

Figure 2. The Nordic contract for 2010 (LNOYR10\_9), the spot price of Brent Blend, year 2009 (LBRENTSPOT\_9), Natural gas contract for 2010 (LNGAS10\_9), Certified emissions reduction for 2010 (LCERDEC10\_9), the German base load contract for 2010 (LDEBL10\_9) Coal contract with delivery in 2010 (LCOAL10\_9) and European allowances for 2010 (LEUADEC10\_9)



<sup>13</sup> Not considering leap years

## 6 Empirical results

This section consists of two parts. The first is a general discussion about the four models used and a short summary of the variables involved. A short discussion of initial lag lengths is also included. The last part is a representation of the econometric results obtained from estimation of the models.

### 6.1 Modeling the forward “year 2010 contract”

The motivation to create four separate models stems from a need to gain experience of the dynamics in the models on a small scale. That is, with data from a single year. The result of the three partial models will also give an indication on what to expect more generally with respect to significance of variables and issues regarding the statistical properties of a larger model. It also gives a unique possibility to analyze and compare the performance of the partial models. In addition we created a model with stacked data from 2007 – 2009 to investigate how OLS and the Autometrics algorithm handle the extreme volatility and shocks of that period. We will also compare this model’s performance with that of the single year models.

The endogenous variable is the Nordic Year contract for 2010 “ $Y_{1,t}$  or NOYR10”. The exogenous variables are: The spot price of North Sea Oil, “ $Y_{2,t}$  or BRENTSPOT\_09”. European allowances delivered in 2010 traded on the Nordic power exchange, “ $Y_{3,t}$  or EUADEC10”, European allowances delivered in 2010 traded on the German power exchange “ $Y_{4,t}$  or EUAEX10”, Certified Emissions Reduction with delivery in 2010. “ $Y_{5,t}$  or CERDEC10”, The German base load contract for 2010 “ $Y_{6,t}$  or DEBL10”, contract for coal delivered in “2010  $Y_{7,t}$  or COAL10”, and contract for gas delivered in 2010 “ $Y_{8,t}$  or NGAS10”. All variables have been converted using the natural logarithm.

The model is using same notation as before, and with the constant suppressed for convenience.

$$\begin{aligned} Y_{1,t} = & \beta_{1,1}Y_{1,t-1} + \dots + \beta_{1,k}Y_{1,t-k} + \beta_{2,1}Y_{2,t} + \dots + \beta_{2,k}Y_{2,t-k} + \beta_{3,1}Y_{3,t} + \dots + \beta_{3,k}Y_{3,t-k} + \\ & \beta_{4,1}Y_{4,t} + \dots + \beta_{4,k}Y_{4,t-k} + \beta_{5,1}Y_{5,t} + \dots + \beta_{5,k}Y_{5,t-k} + \beta_{6,1}Y_{6,t} + \dots + \beta_{6,k}Y_{6,t-k} + \beta_{7,1}Y_{7,t} + \dots \\ & + \beta_{7,k}Y_{7,t-k} + \beta_{8,1}Y_{8,t} + \dots + \beta_{8,k}Y_{8,t-k} + \varepsilon_{1,t} \end{aligned} \quad (5)$$

$$k = 2, 3, \dots, j$$

Equation (5) is a generalization of the conditional model on page (13). The generalization is that we have seven explanatory variables (an underlying VAR with eight variables) and longer lags, i.e.,  $k$  can be 1, but also larger. In the practical model we experimented with several values of  $k$ .

We have estimated four models, one with data from 2009, and another with data from 2008, lastly we made a model with data from 2007. In the first model, Model – 1, with data from 2009, we looked at NOYR10 measured in Euro per MWH, EUADCE10 and EUARE10 measured in Euro per ton, CERDEC10 measured in Euro per unit reduction abroad, DEBL10 measured in Euro per MWH, NGAS10 measured in Euro per MWH, COAL10 measured in US Dollar per ton. We also used the daily (2009) spot price of Brent Blend measured in US Dollar per barrel. All observations are end of day data. Based on this we ran a regression of NOYR10 on EUADCE10, EUARE10, CERDEC10, DEBL10, NGAS, COAL10 and Brent Spot using automatic model selection. Signification level was set to 0.01 and we used dummy saturation to eliminate outliers<sup>14</sup>. One dummy represents one day of observations, i.e. 1 of 232 observations in Model – 1. The results show that all variables and some of the lags are significant even at a 99% level. With only a few exceptions, we obtain t-values that range from 2 and upwards (in absolute value).

Model – 2 includes the same variables. The only difference is that all contracts are traded in 2008. The results are similar, although differences worth mentioning revealed themselves.

Model – 3, with observations from 2007 differs slightly from the others. In this model observations of Certified Emissions and Natural Gas contracts are not included. The reason for this is that the mentioned data was not available when datasets were created. Despite of this, we assume that the model can give insightful information about the price formation in 2007, and that the excluded variables are of minor importance or at least not critical.

Theoretically the removal of a significant variable might pose problems, and this is an issue we might want to address and investigate at a later stage.

Model – 4 represents data from all three years stacked. Observation of Natural Gas and Certified Emission Reduction has been excluded due to missing data.

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<sup>14</sup>See Doornik J. A. (2009)

In the first table below we present a table that summarize the most important aspects of the models discussed above. This is to give the reader a short introduction into what to expect in the following sections. For each model we indicate which period that the observations have been called from. The Variables column describes how many variables that have been included where the numbers in parenthesis is the number of variables. Initial lag length is the number of lags used in the General Unrestricted Model, “GUM” for short. Note that the Autometrics algorithm will remove insignificant lags, thus leaving us with only statistically significant variables. Based on our theory and understanding, we expect to find certain variables and lags in all models, but can not exclude the possibility that we might be surprised with respect to what lags we end up with in the final model. In the last column, an indicator of the overall performance is given. This is based on: i) how many of the included variables ended up in the final model. By the economical intuition presented in chapter three, all variables are important for the model (ad hoc). A situation where few or none are included in the final model might suggest that one or more vital variables are missing and that our model is not very good. However, we must remember that our variables can be of various importance. ii) The interpretability of the implied static long run solutions and the associated t-values for long run elasticity. iii) Misspecification tests and a graphical inspection of the model and results. It is however, a subjective valuation best suited to give the reader an introduction of what to expect. Actual results will be stated explicitly, allowing for individual analysis. There are four performance scores, ranked from worst to best; Poor, Decent, Good and Excellent.

Table 1: An overview of the models used

	<b>Timespan</b>	<b>Variables</b>	<b>Initial lag length</b>	<b>Performance</b>
<b>Model 1</b>	2009	All (8)	10	Good
<b>Model 2</b>	2008	All (8)	10	Good
<b>Model 3</b>	2007	No NGAS and CERDEC (6)	10	Excellent
<b>Model 4</b>	2007-2009	No NGAS and CERDEC (6)	10	Decent

## 6.2 Initial lag lengths

We assume that including lags at this length might give an indication of momentum in the exogenous variables. For example a major importer of coal might at a certain point in time decide to start stocking up as a preparation for winter, this might create a positive sediment in

that market which again can have an effect on the Nordic forward price of electricity. How many lags to include is an open issue. In the pilot model several lag lengths has been experimented on with varying results. In all these experiments the Autometrics algorithm has been applied, resulting in a, for the most time, statistically well behaved final model with several significant variables.

My general impression is that GUMs with a relatively short lag length reduce the number of explanatory variables that are included in the final model. For example using 3 lags in Model – 3 yields a Nordic contract explained only by it self and the German contract with lags. Starting with a GUM with 15 lags, the price of oil, coal and natural gas show up as highly significant variables. The number of dummies is also reduced, which is days with significant impact on the endogenous variable, yet unexplained by the data. We assume that somewhere between 5 and 15 lags is a good choice of lag length in the GUM. Based on experimentation, as well as on our understanding of how fast the information flows in the market, the use of e.g. 25 days will probably not improve the model. However including too many variables is not as bad as including too few, and the Autometrics algorithm easily takes care of the necessary lag reductions. In the below section a standard of 10 lags has been applied. The use of other initial lag lengths will be stated explicitly.

## 6.3 Model – 1 ENOYR10 in 2009

In the first model we looked at observations from the last year of trading before delivery, which includes the last day of trading before actual delivery. All variables were included with ten lags, and the Autometrics algorithm in PcGive 13 was utilized. The results for the final model are presented below, in table 2.

Table 2: Estimation results of Model – 1. The endogenous variable is LNOYR10\_9

Variable	Coefficient	Std.Error	t-value
LNOYR10_9_1	0.801278	0.03353	23.9
LNOYR10_9_2	0.157215	0.02995	5.25
LDEBL10_9	1.16082	0.06176	18.8
LDEBL10_9_1	-1.11673	0.06638	-16.8
LDEBL10_9_9	-0.203205	0.02955	-6.88
LBRENTSPOT_9_3	-0.0370433	0.007912	-4.68
LCOAL10_9	0.207339	0.04962	4.18
LCOAL10_9_1	-0.176442	0.05324	-3.31
LCOAL10_9_8	0.141954	0.02108	6.73

LEUADEC10_9_4	-0.118410	0.03322	-3.56
LEUAEX10_9_5	0.147392	0.03372	4.37
LEUAEX10_9_9	0.0315831	0.01194	2.65
<b>Sigma</b>	0.00942925	<b>RSS</b>	0.0186712439
<b>No. of observations</b>	232	<b>No. of parameters</b>	22
<b>Mean(Y)</b>	3.579	<b>Se(Y)</b>	0.0710485
		<b>No. of Dummies</b>	10

Sigma is the standard deviation of the error term. RSS is the residual sum of squares.

Mean(Y) is the mean of LNOYR10\_9 over the observed period, which is 2009. Subsequently Se(Y) is the standard error of LNOYR10\_9 over the observed period. In a log-linear model, like the one above,  $100 \times \text{sigma}$  is the unexplained standard deviation of the explanatory variable, in per cent.

As a first remark it is worth noting that all included variables shown in the table is significant at the 1% level. The Nordic contract i.e. LNOYR10\_9, is included at the first and the second lag. The value of the first coefficient is 0.801278, which is quite high, and the sum of the coefficients of both lag coefficients is  $\approx 0.9585$ . Formally, it is important that the sum is less than one, otherwise we get into problems that are associated with so called unit-root. Of course 0.96 is seemingly very close to one, and this must be taken into account when we interpret the static long-run solution below.

As expected, German base load i.e. LDEBL10\_9, shows up as highly significant and is represented with two lags, the first with negative sign, and the ninth with positive sign. In addition the contemporaneous observation is statistically significant on the 99 % level with a positive sign. The spot price of “Brent” shows up only in lagged form namely the third lag, which is highly significant. Coal is also represented with the contemporaneous variable, and two lags. European allowances traded on the Nordic power exchange are represented with one significant lag, which happens to be the fourth lag. European allowances traded on the German power exchange are represented with, the fifth and ninth lag. As a final remark I wish to point out the significance of the ninth and eight lag in the variables typical for the German market, the German base load, coal and EUA’s traded in the German market. My point is that there seems to be a connection. But to what extent, I can not say.

The contemporaneous variable ( $t = 0$ ) should all have the same sign because we are looking at input factors, and when the price of an input increases, usually, the price of the final product increase as well. German base load, although not an input in the Nordic contract, should still

have the same  $t = 0$  sign. The reason for this is that it is constructed by the same input factors as the Nordic contract. From the results in table 2 we can confirm this hypothesis.<sup>15</sup> Both Certified Emission reduction and Natural Gas contracts were not significant enough to be included in the final model.

In Model – 1, the only clear relationship is the German base load and the Coal contract's effect on the Nordic contract. Both variables are represented by almost the same lags, which to me suggest that there is a strong relationship between German base load and Coal contracts. This makes sense given the use of thermal power generation in Germany. The effect will spill over into the Nordic market based on the historical and expected future correlation between these markets.

Previously I have stated that I expect to see a relationship between the price of oil and the Nordic contract based on the correlation with coal. Surprisingly this effect is somewhat muted, and is only represented with the third lag of oil. In other words, the effect is there, but not as strong as expected. My explanation is that coal itself is included in the model, and thus there is “no need” for oil. To test this I experimented on Model – 1, and ran the same regression as above without coal (results not posted here) Of course excluding a variable changes the GUM and the dynamics of the model, but it might still give an indication of what to expect. The results were interesting. The contemporaneous observation of oil did show up, in addition to the third lag (again). There were no issues with t-values, misspecification. Signs did make economical sense. The only drawback is that the absolute value of the coefficient “oil” is lower than the coefficient value of “coal”, implying that only some of the effect is captured. I would say that this supports the hypothesis that oil is an indicator of coal.

On the emissions side both EUADEC and EUAEX show up in lagged form. I have no good interpretation for this result other than the fact that the EU ETS system is a market in the early stage with many on-going challenges. It is not necessary always fundamentally driven, and the market experiences political shocks on a regularly basis. None the less it is an input to most of European electricity generation. Therefore we expect to see it represented in the model, one way or the other. We note in particular the relatively high value of the significant coefficients.

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<sup>15</sup> We also made an additional version of Model -1 where the only difference was that we swapped places of the Nordic and the German contract i.e. The German contract was now the endogenous variable. This was to check if the  $t = 0$  observation of the Nordic contract had the same sign as  $t = 0$  of the German contract and coal. It did in fact have the same sign, namely positive.



Natural gas did not show up, which is to some extent as expected. Although used in power generation, natural gas has a high marginal cost. Therefore it will only be used in “Peak load”. That is, it will only come into play when the price is at its highest typically the morning hours and the evening.

Certified emission reduction did not show up, this was not unexpected. I would assume that by that by the time 2009 has passed, all the major power producers have planned their production, and therefore will not need additional “rights to pollute”. On the other side, we should not write it entirely off, there is always some room for adjustments and it might very well show up if we estimate using less strict parameters, for example a 5% critical value.

As a final remark I would mention that the market changes when the contracts close in on delivery date, especially within the last quarter. We have earlier discussed the difference between “the front” and “the curve”. The curve refers to contracts with delivery one year and beyond. The front refers to time periods from tomorrow up to one year.<sup>16</sup> The 2009 model, Model – 1, uses data from the intersection between the curve and the front, and the results should be interpreted with that in mind. It is natural to assume that the closer we get to delivery, the more weight will be put on “the weather” as an explanatory variable(s). The weather might partially or fully “dominate” the model. An example of this might be the weekly status of Scandinavian reservoir levels (water level statistics)<sup>17</sup>. Late in 2009 one can get an idea of what to expect the following year, which again can have a significant impact on the forward Year contract. We have not included this effect in our thesis.

The following table represents a series of tests on the statistical properties of the model. See chapter 4.4 for a more detailed description of the tests function and form.

Table 3: Test battery for Model - 1

<b>Test</b>	<b>Test statics</b>	<b>Value</b>	<b>p-value of tests</b>
AR 1-2 test	F(2,208)	0.18692	0.8297
ARCH 1-1 test	F(1,230)	0.36159	0.5482
Normality test	Chi^2(2)	0.26389	0.8764
Hetero test	F(24,197)	0.81426	0.7163
RESET23 test	F(2,208)	1.4344	0.2406

<sup>16</sup> There is no official definition on what «the curve» and «the front» is. I have stated a rough generalization and based my discussion on it. Others may have other interpretations. None the less, there is a difference and therefore we might agree on the division, at least in theory.

<sup>17</sup> See <http://www.nve.no/no/Nyhetsarkiv-/Vassmagasinstatistikk/> for examples.

As we can see from the table above, there are no issues with serial correlation, heteroskedasticity or the normality assumption.

Model – 1 can in principle be solved for LNOYR10\_9 as a function of the levels of the explanatory variables. The parameter of the long run equation has the interpretation of long run elasticities.

Table 4: Solved static long-run equation for LNOYR10\_9 from Model – 1.

<b>Variable</b>	<b>Coefficient</b>	<b>Std.Error</b>	<b>t-value</b>
LDEBL10_9	-3.83336	1.816	-2.11
LBRENTSPOT_9	-0.892452	0.4114	-2.17
LCOAL10_9	4.16437	1.652	2.52
LEUADEC10_9	-2.85275	1.695	-1.68
LEUAEX10_9	4.31190	2.163	1.99

Table 4 shows that the static long run does not yield an interpretable result which is suggestive of a unit root problem, i.e. that the sum of autoregressive coefficients is unity. This is confirmed by re-estimation Model – 1 as an equilibrium correction model. The estimated equilibrium correction coefficient is -0.04 and the t-value is -2.09 which is insignificant when the null hypothesis is a unit root, cf. the critical values in Table 1 in MacKinnon (1991). The conclusion is that the model presented in table 2 is a relevant model for the change in LNOYR10\_9, but not a relevant model for the level of the contract over this sample.

Below we can see a graphical representation of the dynamic multipliers and the interim multiplier of all the significant variables in the final model. The first column is the effect of a temporary shock to a variable, and how the shock “dies out” as time passes. The second column is the cumulative effect. The rows are as follows; “LDEBL10\_9” the German year contract, “LBRENTSPOT\_9” spot price of Brent oil “LCOAL10\_9” Coal for delivery in 2010, “LEUADEC10\_9” European allowances traded on the Nordic power exchange and “LEUAEX10\_9” European allowances traded on the European energy exchange. We choose to report these results despite the fact that the static long-run equation is invalid. In particular the short term dynamics is of interest, as it can give us an impression of how a variable shock dies out over time.

Figure 3 The dynamic multipliers and the interim multiplier of Model – 1 in Table 2.

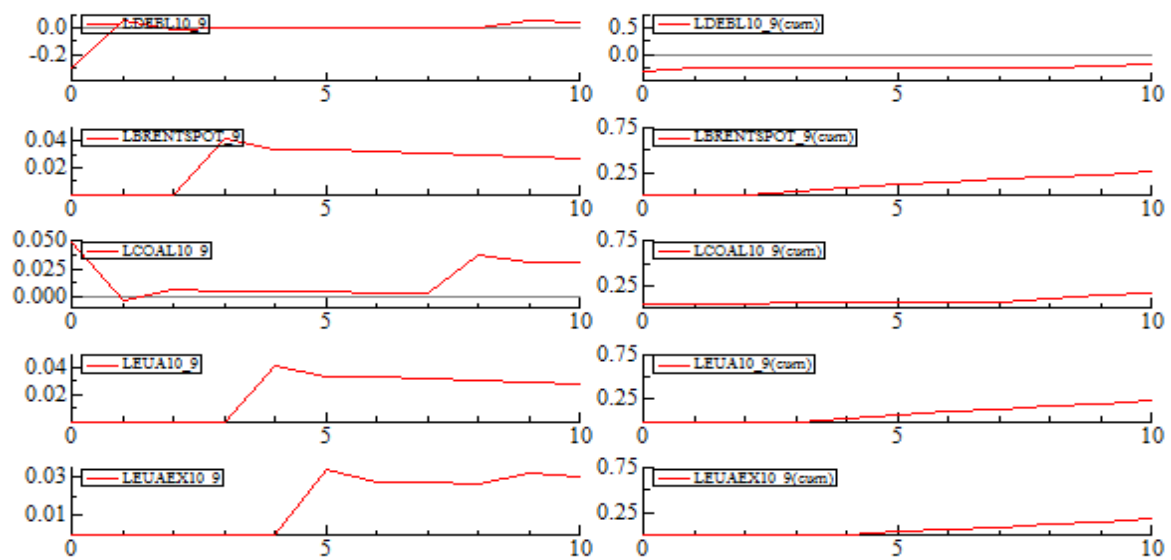
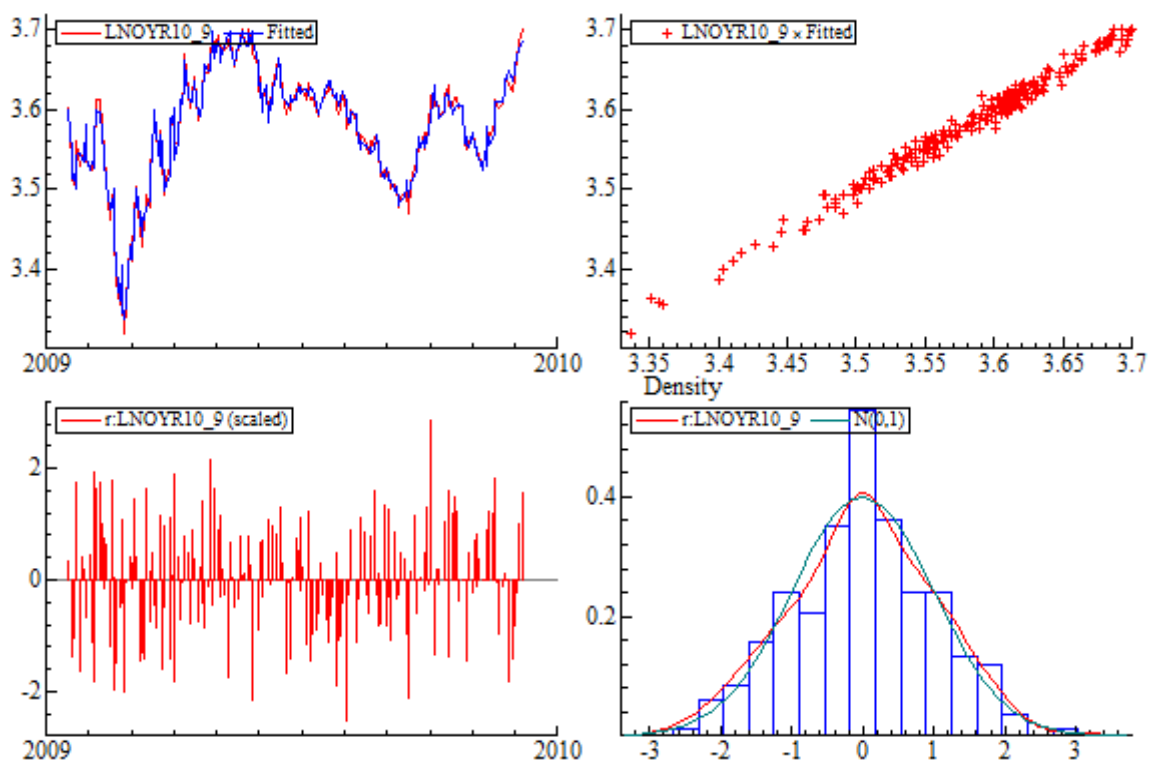


Figure 4. Panel a) Actual and fitted observations. Panel b) Scatterplot of actual and fitted observations. Panel c) Scaled residuals. Panel d) Histogram of the disturbances, estimated density and theoretical standard normal density.



## 6.4 Model – 2 ENOYR10 in 2008

In the second model observations two years from delivery was investigated. That is, the contract for delivery of electricity in 2010 traded in 2008. All variables were included with ten lags, and the Autometrics algorithm in PcGive 13 was utilized. The results for the final model are presented below, in table 5.

Table 5: Econometric results Model – 2 The endogenous variable is LNOYR10\_8

Variable	Coefficient	Std.Error	t-value
LNOYR10_8_1	0.978738	0.02448	40.0
LNOYR10_8_7	-0.121696	0.03451	-3.53
LNOYR10_8_10	0.0839388	0.02971	2.83
LDEBL10_8	0.851205	0.06102	13.9
LDEBL10_8_1	-1.05709	0.08066	-13.1
LDEBL10_8_2	0.230011	0.06358	3.62
LDEBL10_8_3	0.331778	0.08587	3.86
LDEBL10_8_4	-0.455106	0.07716	-5.90
LDEBL10_8_7	0.321903	0.05638	5.71
LDEBL10_8_9	-0.158421	0.04291	-3.69
LBRENTSPOT_8_6	0.0868773	0.02133	4.07
LBRENTSPOT_8_7	-0.0571554	0.02146	-2.66
LCOAL10_8	0.213912	0.03566	6.00
LCOAL10_8_1	-0.183999	0.04259	-4.32
LCOAL10_8_3	-0.186611	0.04484	-4.16
LCOAL10_8_4	0.132553	0.04028	3.29
LNGAS10_8_3	-0.135868	0.04475	-3.04
LNGAS10_8_4	0.231006	0.05308	4.35
LNGAS10_8_7	-0.0922253	0.03143	-2.93
LEUADEC10_8_3	-0.124625	0.03348	-3.72
LEUADEC10_8_5	-0.343901	0.07900	-4.35
LEUADEC10_8_7	-0.122244	0.02872	-4.26
LEUAEX10_8_4	0.165411	0.04025	4.11
LEUAEX10_8_5	0.325378	0.08232	3.95
LEUAEX10_8_9	0.144712	0.03225	4.49
LCERDEC10_8	0.112646	0.02972	3.79
LCERDEC10_8_1	-0.104321	0.03937	-2.65
LCERDEC10_8_2	-0.156948	0.04196	-3.74
LCERDEC10_8_3	0.177002	0.03025	5.85
<b>Sigma</b>	0.00807156	<b>RSS</b>	0.0128345558
<b>No. of observations</b>	234	<b>No. of parameters</b>	37
<b>Mean(Y)</b>	3.97091	<b>Se(Y)</b>	0.138437
		<b>No. of Dummies</b>	7

As a general observation regarding signs we observe that the contemporaneous variables (the ones that have been included) have a positive sign, this is to be expected and makes economic sense. Lagged variables have various signs, which is also to be expected.

Similar to model 1, all variables included in the final model are significant at the 99% level. The Nordic contract is represented with three lags, the first, seventh and tenth, which sum up to  $\approx 0,941$ , a number quite close to 1.

The “German contract” is represented with six separate lags and the contemporaneous observation. Brent Blend oil-price is represented with the sixth and seventh lag. The coefficient is relatively small compared with the other variables. Coal is represented with the contemporaneous observations and three separate lags. All have an intuitive sign. Natural gas is represented with lagged observations only, which are both positive and negative. LEUADEC and LEUAEX show up in lagged form. Taken together they are represented with five lags (not counting the fifth lag twice). Both positive and negative signs are represented. Certified emission reduction (LCERDEC) is represented with the contemporaneous variable, and lag 1-3. Signs are intuitive and make sense economically.

Uniquely to this model, we observe that all variables are represented, and that more lags have been included.<sup>18</sup> I partially contribute this to the initial shock of the financial crisis and the following period of volatility. More uncertainty about the future might induce statistically significant “up and down” movements. In fact we observe a clear “up followed by down” movement in almost all variables. In addition we expect an elevated sensitivity for movements in the market, which again can be amplified by the fact that we now are two years from delivery. Therefore input factors are our best and maybe only indication of future price.

Surprisingly oil is only represented by the sixth and seventh lag, and not the contemporaneous observation. I would have expected that the very liquid and international oil market would have showed up more explicitly as an indicator, and not only in lagged form. We might speculate that coal nullify the effect of oil, similar to that of model -1 (although not tested in this model).

We can also see that Certified Emission Reductions (CERDEC10) has shown up as a good explanatory variable, represented by the contemporaneous variable and the first three lags.

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<sup>18</sup> Remembering that Autometrics has been utilized and that the initial settings are the same for all models

CER's are, in the same way as EUA's, "a price of pollution". One can look upon it as a price on the negative externality that, for example a coal fueled power plant, imposes on the environment and its surroundings. An electricity producer will have to incorporate "the cost of polluting" into the general cost function of his portfolio of production units. It is hard to say why CER's show up as highly significant in Model – 2, and not 1. The market for emissions is complex, and I can only speculate as to what the reasons are. Market confidence might play a role. As mentioned earlier, politics do matter, and play a role in the future of both the CER and EUA emissions trading scheme. Certainty and or uncertainty in one as opposed to the other can make a difference in the preferences of market participants. A lack of trust in the CER system in 2009, and not 2008 could be the cause. Expectations of future price of pollution, and the state of the macroeconomic situation in Europe can play a role. This again can induce participants to postpone purchases, or shift preferences with regards to "the cost of pollution".

The only clear conclusion we can draw is the fact that pollution i.e. EUA and CER's explain variation in the endogenous variable. It affects the cost side of production, which again change the price of the final product, electricity. As a whole, "pollution" is represented by the contemporaneous observation and the first five lags. In addition the seventh and ninth lag is significant. Over the course of almost two weeks (10 lags), pollution almost daily contributes to variation in LNOYR10. Therefore we conclude that pollution is a very important variable in the energy mix.

Table 6: Test battery for model - 2

<b>Test</b>	<b>Test statics</b>	<b>Value</b>	<b>p-value of tests</b>
AR 1-2 test	F(2,195)	0.066006	0.9361
ARCH 1-1 test	F(1,232)	0.23812	0.6260
Normality test	Chi^2(2)	0.34515	0.8415
Hetero test	F(60,166)	0.68973	0.9509
RESET23 test	F(2,195)	3.1488	0.0451

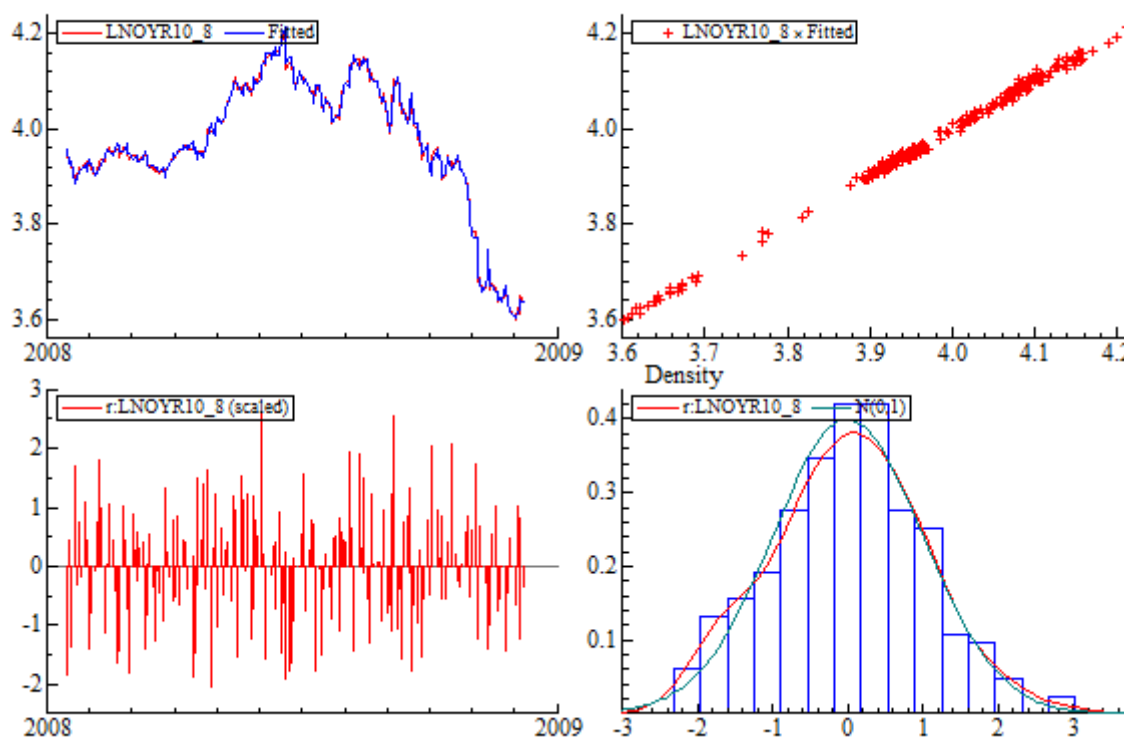
Table 6 shows that there are no serious issues with respect to misspecification of the model. We observe that RESET23 test fails on 5% critical value, but not on 1% critical value.

Table 7: Solved static long-run equation for LNOYR10\_9 from Model – 2

Variable	Coefficient	Std.Error	t-value
LDEBL10_8	1.08918	0.1950	5.58
LBRENTSPOT_8	0.503596	0.2081	2.42
LCOAL10_8	-0.409098	0.3225	-1.27
LNGAS10_8	0.0493480	0.2707	0.182
LEUADEC10_8	-11.5477	4.354	-2.65
LEUAEX10_8	10.7677	4.004	2.69
LCERDEC10_8	0.480836	0.2573	1.87

Table 8 shows that the static long run does not give interpretable results, hence we are in the same situation as in Model – 1, namely that the model is a model for short run variations. In order to save space, the dynamic multiplier is therefore not reported for Model – 2.

Figure 5. Panel a) Actual and fitted observations. Panel b) Scatterplot of actual and fitted observations. Panel c) Scaled residuals. Panel d) Histogram of the disturbances, estimated density and theoretical standard normal density.



In panel d) a near perfect match with  $N(0,1)$  on the positive side in this model. A bit more tail risk on the negative side.

## 6.5 Model – 3 ENOYR10 in 2007

In the third model observations that are three years from delivery was investigated. That is, the contract for delivery of electricity in 2010 traded in 2007. In this model, only LNOYR10, LDEBL10, LCOAL10, LEUADEC and LEUAEX were included. The reason for this is that no contract for LCERDEC and LNGAS for 2010 existed in 2007 (as far as I know) .

The results for the final model are presented below, in table – 7

Table 8: Table of results model – 3 The endogenous variable is LNOYR10\_7

<b>Variable</b>	<b>Coefficient</b>	<b>Std.Error</b>	<b>t-value</b>
LNOYR10_7_1	0.812289	0.03294	24.7
LNOYR10_7_7	0.129511	0.03049	4.25
LNOYR10_7_9	-0.0886352	0.02836	-3.13
LDEBL10_7	0.412801	0.06584	6.27
LDEBL10_7_1	-0.466475	0.07800	-5.98
LDEBL10_7_2	0.305198	0.06927	4.41
LDEBL10_7_3	-0.176332	0.05957	-2.96
LDEBL10_7_5	-0.254787	0.06216	-4.10
LDEBL10_7_6	0.264354	0.05332	4.96
LCOAL10_7	0.0637385	0.01287	4.95
LCOAL10_7_10	-0.0347347	0.01174	-2.96
LEUADEC10_7	0.0886253	0.01217	7.28
LEUADEC10_7_1	-0.0750884	0.01306	-5.75
LEUAEX10_7_10	0.0183685	0.005552	3.31
<b>Sigma</b>	0.0034176	<b>RSS</b>	0.00241776317
<b>No. of observations</b>	232	<b>No. of parameters</b>	25
<b>Mean(Y)</b>	3.82874	<b>Se(Y)</b>	0.0634713
		<b>No. of Dummies</b>	11

The final model again consists of highly significant variables represented by the contemporaneous observation and lags. The lagged values of the Nordic contract sum to 0,853 which is lower than for Model – 1 and Model – 2, and is suggestive that a relationship in levels can be sustained. The explanatory variables have interpretable signs and reasonable coefficient sizes.

In Model – 3 we are three years from delivery, therefore the impact of “weather”, I would assume, is very small. Therefore we expect to see a model entirely based on the forward market of fuels and the cost side of production. Ironically, when moving away in time, we are able to catch more of the available information, relatively speaking. An econometrical model



might do better the further away from delivery we go. As opposed to a situation close to delivery where the vital “weather aspect” is excluded.

It is also interesting to observe that all the contemporaneous observations are included<sup>19</sup>. This implies that “what happens today matters today” which to me is more intuitively than representation by lags only. It also supports the theoretical financial of strong market efficiency, or that “the market” prices in all relevant information immediately (an ambiguous claim I might add).

The German base load contract for 2010 is an important explanatory variable, we assume that the historical and expected future correlation is one explanation for this, we have also hypothesized that the net flow of electricity goes from the Nordic region to Germany (and the continent), which results in price correlation.

Input factors are here represented by (highly significant) coal and emissions. The absolute values of these variables are relatively low, which makes sense given the energy mix in the Nordic region which is dominated by hydropower and only partially by coal.

Table 9: Test battery for Model – 3.

Test	Test statics	Results	p-value of tests
AR 1-2 test	F(2,205)	0.73725	0.4797
ARCH 1-1 test	F(1,230)	0.93036	0.3358
Normality test	Chi <sup>2</sup> (2)	1.4663	0.4804
Hetero test	F(28,192)	1.4228	0.0879
RESET23 test	F(2,205)	0.13205	0.8764

As we can see from the table with the battery of misspecification tests, there are no issues with serial correlation, heteroskedasticity or the normality assumption.

Table 10: Solved static long-run equation fro NOYR10\_7 from Model – 3

Variable	Coefficient	Std.Error	t-value
LDEBL10_7	0.577231	0.02689	21.5
LCOAL10_7	0.197525	0.02981	6.63
LEUADEC10_7	0.0921911	0.03074	3.00
LEUAEX10_7	0.125096	0.03055	4.10

<sup>19</sup> Strictly speaking we lack the t=0 observation of LEUAEX10, but as it is the same product as LEUADEC10 we can speak of them as one.

Table 10 shows that the static long run solution makes good sense for Model – 3. Generally this refers to a situation where variation in LNOYR10 and LDEBL10\_7 has “stopped” (in theory), as it is the long run, i.e. the sum of all previous changes. “Long-run coefficient” is a representation of the change in LNOYR10 caused by a permanent change in LDEBL10\_7. This interpretation is supported by calculating the unit-root test that we used for Model – 1. The test static is -5.98 which may be formally significant when judged against the critical value in MacKinnon (1991)

Figure 6 - Graphical analysis of the dynamic multipliers and the interim multiplier of all variables. Observations are from 2007

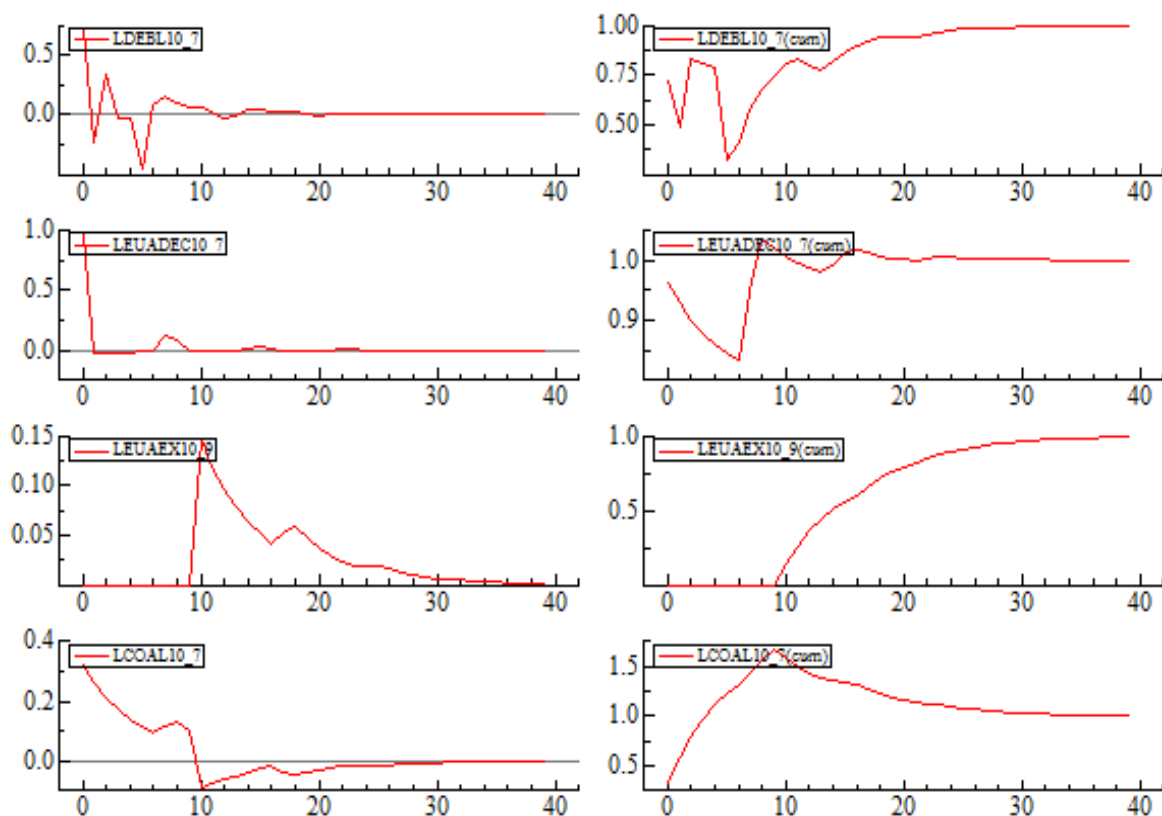
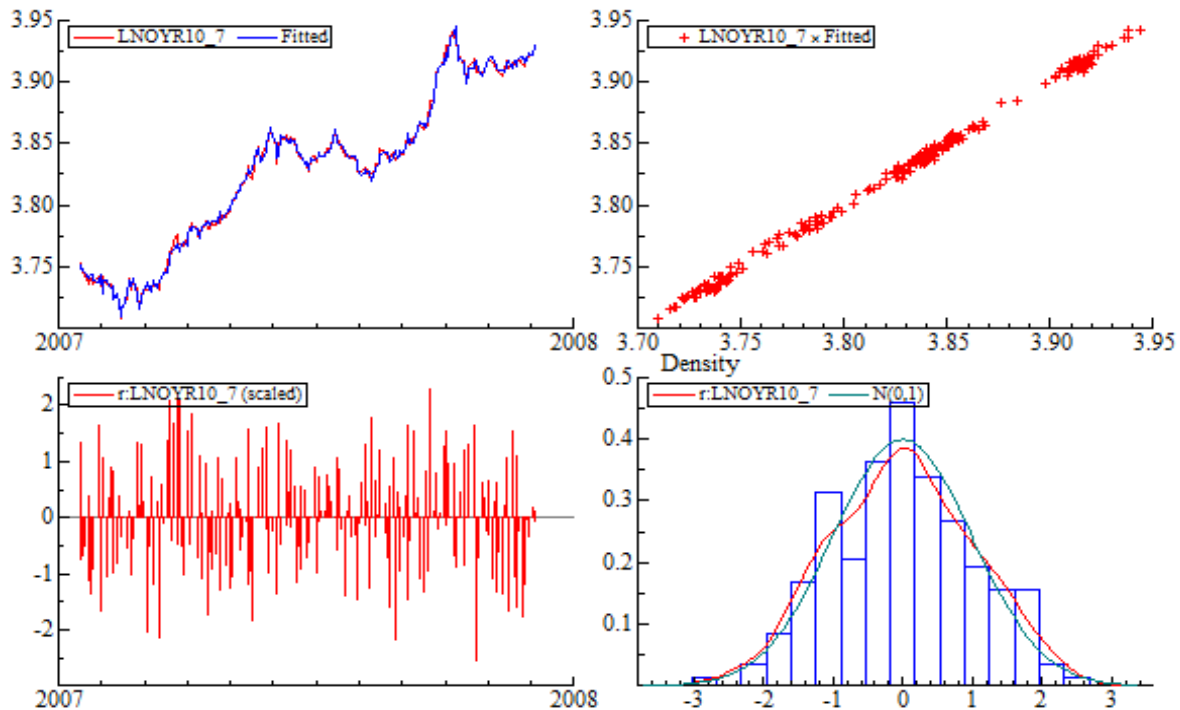


Figure 7. Panel a) Actual and fitted observations. Panel b) Scatterplot of actual and fitted observations. Panel c) Scaled residuals. Panel d) Histogram of the disturbances, estimated density and theoretical standard normal density.



## 6.6 Model – 4 ENOYR10 from 2007 to 2009 (stacked)

In the fourth model observations from three years up to delivery investigated, in other words a model of the stacked data. We included LNOYR10, LDEBL10, LCOAL10, LEUADEC and LEUAEX. The results of the final model is presented below, in table 10.

Table 11: Table of results model – 4 The endogenous variable is LNOYR10\_Stack

Variable	Coefficient	Std.Error	t-value
LNOYR10_Stack_1	0.996868	0.01318	75.6
LNOYR10_Stack_5	0.100699	0.01722	5.85
LNOYR10_Stack_6	-0.104645	0.01810	-5.78
LDEBL10_Stack	0.777037	0.03538	22.0
LDEBL10_Stack_1	-0.920573	0.04542	-20.3
LDEBL10_Stack_2	0.123552	0.02590	4.77
LDEBL10_Stack_6	0.219323	0.03254	6.74
LDEBL10_Stack_7	-0.104805	0.02779	-3.77
LDEBL10_Stack_9	-0.0829791	0.01721	-4.82
LCOAL10_Stack	0.143551	0.02137	6.72
LCOAL10_Stack_1	-0.145043	0.02333	-6.22
LCOAL10_Stack_6	-0.0908688	0.01729	-5.26

LCOAL10_Stack_8	0.0803970	0.01348	5.97
LBRENT_SPOT	0.0444592	0.01007	4.42
LBRENT_SPOT_1	-0.0507612	0.01084	-4.68
LBRENT_SPOT_6	0.0585716	0.01102	5.31
LBRENT_SPOT_7	-0.0401126	0.01009	-3.98
LEUADEC10_Stack	0.0661152	0.01130	5.85
LEUADEC10_Stack_1	-0.0568214	0.01198	-4.74
LEUADEC10_Stack_8	0.0335095	0.01021	3.28
LEUAEX10_Stack	-0.0490308	0.01132	-4.33
<b>Sigma</b>	0.00609903	<b>RSS</b>	0.0226165107
<b>No. of observations</b>	718	<b>No. of parameters</b>	110
<b>Mean(Y)</b>	3.79326	<b>Se(Y)</b>	0.18865
		<b>No. of Dummies</b>	89

As we can see from table 14, all variables are statistically significant at the 99% level, and all variables initially included also show up in the final model. We should also note that the contemporaneous observation of all variables is highly significant and included in the final model. Signs of variables and lags make economically and intuitively sense. Except the  $t=0$  observation of EUAEX which is negative. It should have the same sign as EUADEC. I base this on the fact that it is the same product, although traded on separate exchanges. However, if we collapse EUADEC and EUAEX the end result is positive, which is what we expect.

The Nordic contract with lag one, five and six is represented. They sum up to  $\approx 0,992$ . We understand that, similar to Model – 1 and, we will get issues with unit-root and the static long run solution.

The German base load contract is represented with five separate lags in addition to the contemporaneous observation.

Coal is represented by the contemporaneous observation, the first, sixth and eight lag.

Both the European allowances (EUADEC10 and EUAEX10) are represented by the contemporaneous observation. In addition the EUADEC10's first and eight lag show up in the final model.

The motivation to include a stacked version of all observations from 2007 – 2009 was to see how OLS and Autometrics would tackle the drastic changes in the market in this period. The strong upward market in 2007 followed by the sharp drop in 2008, and the “new market” in 2009 is a challenge for OLS. One could say that 2008 represented a regime shift or a correction, and 2009 is the beginning of a new trend.

Based on lack of meaningful and interpretable results, the static long solution and the graphical presentation of dynamic multipliers and the interim multiplier are not reported.

On the positive side, we observe that all contemporaneous observations are present and highly significant. Model – 4 is a very good presentation of the dynamic relationships in the Nordic electricity market over many years, and based on a large amount of data. We recognize the classic up and down movements often observed in financial markets. The illusive oil variable is also strongly represented, both by the contemporaneous observation and the first, sixth and seventh lag. The absolute value of the coefficient is similar to that of emissions. This supports the assumption that oil is used as an indicator in the Nordic electricity market, which we also assumed in chapter two. We find support for this in table 13 where  $\text{Corr}(\text{LBRENT\_SPOT}, \text{LCOAL10\_Stack}) = 0.73834$

The following table represents a series of tests on the statistical performance of the model. See chapter 4.4 for a more detailed description of the tests function and form.

Table 12: Test battery for model - 4

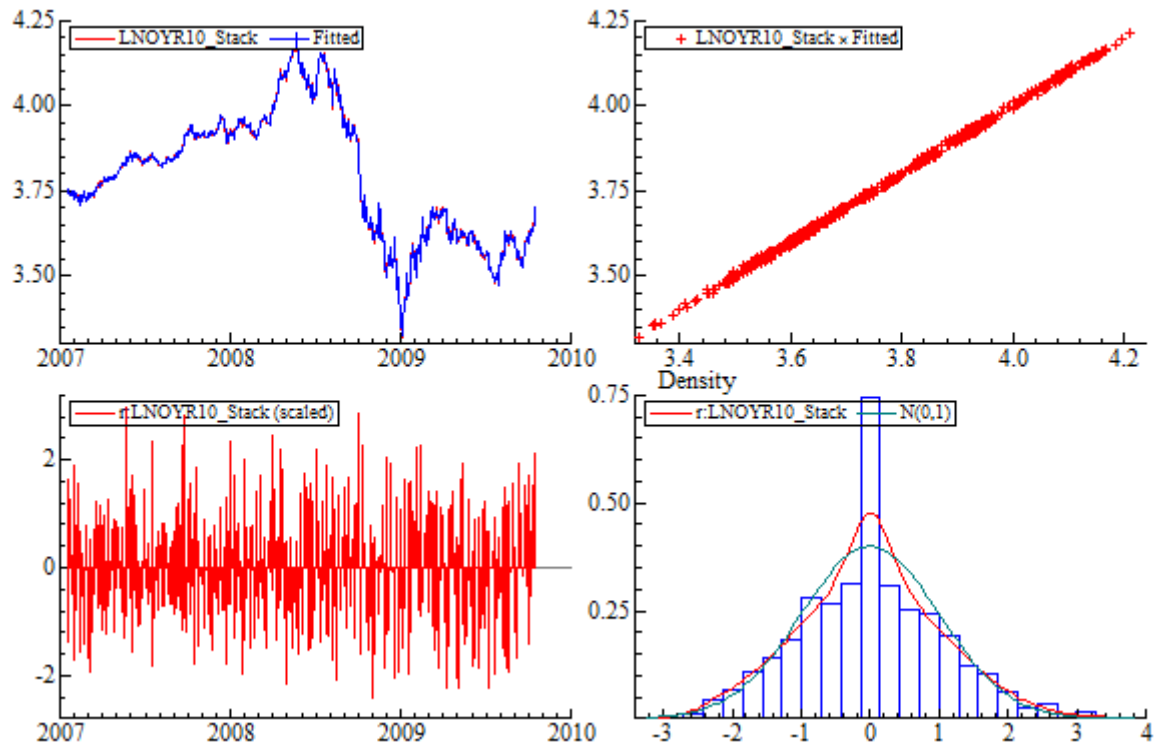
Test	Test statics	Results	p-value of tests
AR 1-2 test:	F(2,606)	0.86086	0.4233
ARCH 1-1 test:	F(1,716)	0.33308	0.5640
Normality test:	Chi <sup>2</sup> (2)	2.3510	0.3087
Hetero test:	F(42,586)	1.4207	0.0447
RESET23 test:	F(2,606)	2.1710	0.1150

We can see a slight issue with hetroscedasticity, but a significance level of 95% should solve the problem.

Table 13: Correlation matrix of all variables in Model – 4.

Historic correlation all variables year 2007-2009						
<b>LNOYR10_Stack</b>	1.0000					
<b>LEUADEC10_Stack</b>	0.94343	1.0000				
<b>LBRENT_SPOT</b>	0.80247	0.79710	1.0000			
<b>LDEBL10_Stack</b>	0.90162	0.81465	0.66699	1.0000		
<b>LCOAL10_Stack</b>	0.75321	0.64347	0.73834	0.88954	1.0000	
<b>LEUAEX10</b>	0.94498	0.99954	0.79881	0.81460	0.64238	1.0000

Figure 8. Panel a) Actual and fitted observations. Panel b) Scatterplot of actual and fitted observations. Panel c) Scaled residuals. Panel d) Histogram of the disturbances, estimated density and theoretical standard normal density.



# 7 Instrumental Estimation

In this chapter we will re-estimate Model – 3, using the method of Generalized Instrumental Variables (GIV) or two stage least squares (2SLS). This estimation method are used when estimating models with endogenous explanatory variables, as is the case in Model – 3 where the German base load contract can be interpreted as an endogenous explanatory variable.

The motivation to re-estimate Model – 3 stems from the assumption that in a simultaneous equation system, all endogenous variables are correlated with all errors in that system. This might lead to a bias in the OLS estimators that will not disappear, even in large samples.

## 7.1 Important aspects when using Instrumental variables and two stage least squares

There are two important aspects to remember when using instrumental variables. First and most important the instrument “Z” should be correlated with the variable “X” which it is to be an instrument for. In addition we prefer strong to weak correlation. This is because we want the instrument to explain as much as possible of the variation in the variable it is to be an instrument for. Lastly the instrument should not be correlated with the disturbance term.

Formally:

$$\text{Cov}(Z, Y_{k,t}) \neq 0 \text{ and } \text{Cov}(Z, \varepsilon_t) = 0$$

For the equation system to be identified we need at least one instrument for each endogenous variable. In the case of over-identification, 2SLS (which is the same as GIVE), is an optimal IV estimator based on a weighted set of the available instruments.

A drawback with the IV is that the variance of the coefficient estimates is higher than with OLS. This is a result of the fact that only a portion of the variation in the endogenous variable (which we have an IV for) is used to estimate the slope. This is also the reason that we prefer strong instruments, in order to minimize the variance of the IV estimator.

## 7.2 Model – 3.1 Estimation with Instrumental Variables

Table 14: Results Model – 3.1 with IV-estimation. The endogenous variable is LNOYR10\_7

Variable	Coefficient	Std.Error	t-value
LNOYR10_7_1	0.842402	0.03269	25.8
LNOYR10_7_7	0.145852	0.03571	4.08
LNOYR10_7_9	-0.128146	0.03240	-3.95
<b>LDEBL10_7 Y</b>	0.680162	0.2277	2.99
LDEBL10_7_1	-0.711103	0.2089	-3.40
LDEBL10_7_2	0.308866	0.07298	4.23
LDEBL10_7_3	-0.218522	0.06714	-3.25
LDEBL10_7_5	-0.237274	0.06877	-3.45
LDEBL10_7_6	0.257802	0.05719	4.51
LCOAL10_7	0.0290260	0.006740	4.31
LEUADEC10_7	0.0626117	0.02706	2.31
LEUADEC10_7_1	-0.0541286	0.02612	-2.07
LEUAEX10_7_10	0.0210369	0.006593	3.19
<b>sigma</b>	0.00359865	<b>no. endogenous variables</b>	2
<b>Reduced-form sigma</b>	0.0037164	<b>no. of observations</b>	232
<b>mean(LNOYR10_7)</b>	3.82874	<b>no. of instruments</b>	31
<b>se(LNOYR10_7)</b>	0.0634713	<b>no. of parameters</b>	24
<b>RSS</b>	0.00269366089	<b>no. of dummies</b>	11

Additional instruments are: LCOAL10\_7\_10, LCOAL10\_7\_8, LNOYR10\_7\_8, LEUADEC10\_7\_5, LEUAEX10\_7\_5, LEUAEX10\_7\_8, LDEBL10\_7\_7 and LNOYR10\_7\_5.

Because we in essence are re-estimating Model – 3, the economical interpretation of the variables and of the model is the same as above. Therefore, we will not repeat ourselves and state them again. In stead we will focus on the difference of the two results in light of OLS and IV estimation. Of special interest is the variable LDEBL10\_7 who in Model – 3 were exogenous, but in Model – 3.1 is endogenous.

Our first observation is that the coefficient of “LDEBL10\_7” is substantially higher when using IV-estimation (0.68) than OLS (0.41). We have already stated that using OLS in simultaneous equation systems might lead to a bias, which can be corrected by using instrument variables. A t-value of 2.99 is good enough for statistical significance even on the 1% level. An issue with higher variance of the IV-estimator might explain why we register a somewhat lower t-value in Model – 3.1 than 3 We can therefore conclude that the OLS



estimation in Model – 3 underestimate the coefficient value of the contemporaneous observation of the German base load contract.

We can also see some changes in the coefficient value of the other variables. But this is to be expected as we have used some of them as instruments in our IV-estimation. In addition OLS bias affects all the coefficient estimators of the model.

The way we have found the, hopefully strong, instruments deserves more explanation. Several manual operations has been undertaken to find the best suited instrument(s). Firstly we regressed LDEBL10\_7 on lags of LDEBL10\_7, to find highly significant lags not present in Model – 3. We also used the Autometrics algorithm to suggest suitable lags to be used as IV's. Lastly we made use of the Autometrics algorithm available for IV estimation to get a suggestion of suitable IV's. After some trial and error we ended up with Model – 3.1 where we also had to use two exogenous lags from Model – 3 as instruments.

Table 15: Test battery for Model – 3.1 IV-estimation

Test	Test statics	Results	p-value of tests
AR 1-2 test:	F(2,206)	0.31732	0.7285
ARCH 1-1 test:	F(1,230)	0.68803	0.4077
Normality test:	Chi <sup>2</sup> (2)	2.4961	0.2871
Hetero test:	F(26,194)	1.2518	0.1963
RESET23 test:	Not reported	Not reported	Not reported
Specification test:	Chi <sup>2</sup> (7)	10.539	0.1600
Testing beta = 0:	Chi <sup>2</sup> (23)	71636	0.0000

The test battery has been expanded by two additional tests, namely the “Specification test” and “Testing beta = 0”

The Sargan test or “specification test” for endogeneity tests the hypothesis that the instruments are correlated with the residual. The test is due to Sargan (1958) and Sargan (1964). If the instruments are valid, they will not have explanatory power in an auxiliary regression with the residual from the IV-estimation as the exogenous variable. The result of the “specification test” is arrived at by multiplying the “ $R^2$ ” from the auxiliary regression with the number of observations “ $n$ ”. We note that in this case the Sargan test is a Chi square distribution with seven degrees of freedom. We also note that the test is insignificant in our case. The null hypothesis is that the instruments are valid. This suggests that the instruments are valid and that the structural equation is correctly specified.

As a minimum we need one instrument per endogenous variable. In our case, we have many instruments, which suggest that we have over-identification. But an over identified equation is identified, which is the minimum criterion for identification. The rank - and order condition are useful tools for further investigation.

Testing  $\beta = 0$  is a test for weak instruments. As noted before we want the instrument to be correlated with the variable it is to be an instrument for. This can be tested with a t-test if we have one instrument or an F-test if there is more than one. We want to know if the instruments exhibit joint explanatory power over the target variable. Therefore our null hypothesis is:

$$H_0: \beta_1 = 0, \beta_2 = 0, \beta_k = 0 \text{ versus } H_1: H_0 \text{ not true}$$

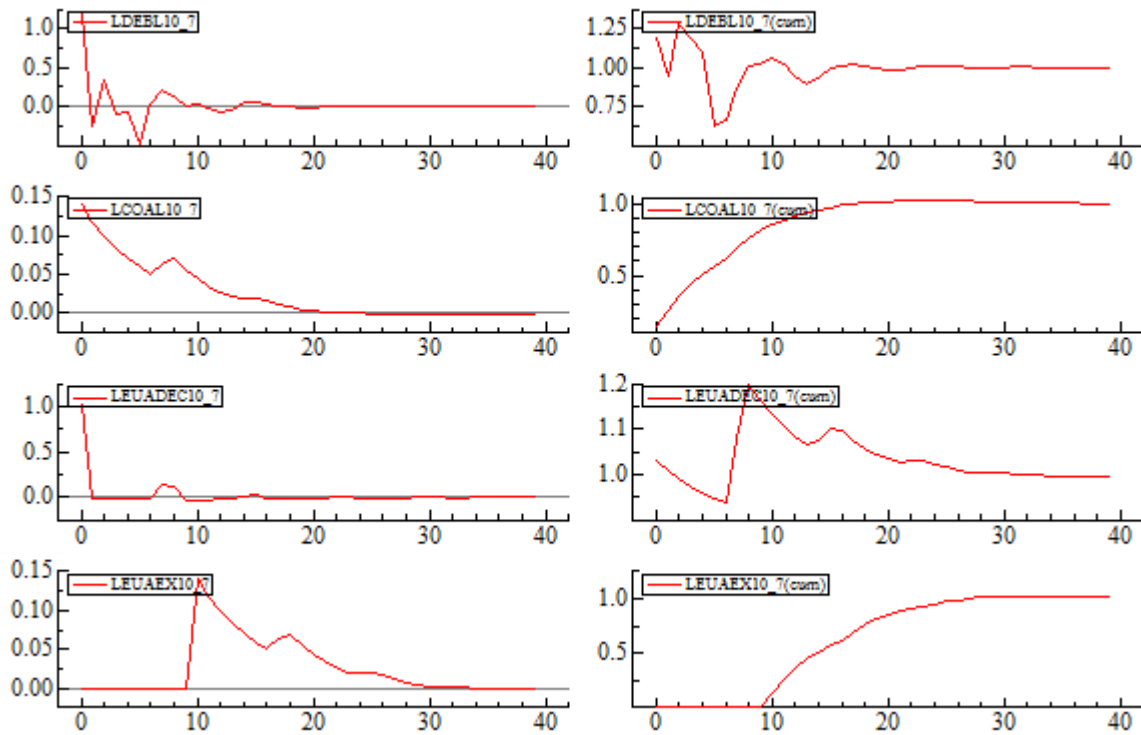
We can see that in our case the null is rejected at the 99% level and can conclude that at least one instrument is valid.

Table 16: Solved static long-run equation for NOYR10\_7 from Model – 3.1

Variable	Coefficient	Std.Error	t-value
LDEBL10_7	0.571379	0.03424	16.7
LCOAL10_7	0.207489	0.03620	5.73
LEUADEC10_7	0.0606399	0.03625	1.67
LEUAEX10_7	0.150380	0.03653	4.12

The static long run solution from Model – 3.1 is quite similar to that of Model – 3. The coefficients are slightly different, and t-values have changed. It is not surprising as the model has changed in the sense that variables have been removed and or used as IV, we have also included new instruments not present in Model – 3.

Figure 9 - Graphical analysis of the dynamic multipliers and the interim multiplier of all variables using instrumental variable estimation. Observations are from 2007



Of interest in figure 8 is the change in LDEBL10\_7, more specifically in the interim multipliers. The shape is similar to that of figure 6, but there seems to have been a shift up which is consistent with the assumption that OLS underestimates the effect of the German base load contract. There are slight differences in the other graphs as well, but they can probably be contributed to the differences in variable use in Model – 3 and 3.1.

## 8 Conclusions

This thesis has made use of dynamic models of time series data to analyze the forward Nordic year contract for 2010. My goal was to gain knowledge of the fundamentals in the market, and to derive statistically significant results with respect to fuel and electricity prices. I claim to have reached my goals. The thesis has utilized a general to specific framework to create five models of the Nordic 2010 contract, spanning over three years 2007-2009. Together they reveal an interesting relationship between the endogenous and exogenous variables.

Model – 1 investigates the relationship between the Nordic contract for 2010 and assumed explanatory variables as they were in 2009. Models – 2 and 3 are similar representations of 2008 and 2007. Model – 4 is a stacked version with observations spanning from 2007 to 2009. Model – 3.1, the last- or fifth model, is a re-estimation of Model – 3 using instrumental variables and two stage least squares.

I have used daily observations (high frequency data) from the forward market, focusing on the cost side of electricity production. Coal, emissions, natural gas and oil have been used as exogenous variables in addition to the German base load contract for 2010.

As my empirical findings show, there is a strong relationship between the explanatory variables – or the cost side of electricity production, and the final product “electricity”. There are however interesting differences between the models for the different data sets.

For the 2009 data set, I find a clear relationship between coal and the Nordic contract. The same applies in relation to the German contract. “The market” seems to instantly take into account price changes and translate it on to the Nordic contract. The cost of pollution (European allowances and certified emission reductions) is also represented among the explanatory variables, but only in lagged form. Apparently there is a delayed but significant response to changes in the emissions market onto the Nordic contract. Lastly I have assumed that the closer we get to delivery on the 1. January 2010, the more will “weather” and other variables not included in the models we have estimated affect our endogenous variable. That is, unexplained volatility with significant explanatory power. Model – 1 gives a good fit, although this model essentially explains the daily change in the contract. A unit-root cannot be rejected and a log term solution cannot be inferred from this model.

The financial crisis of 2008 did reach the electricity market as well. A simple inspection of figure 5 confirms this, and we note a substantial reduction in the forward price of electricity. An inspection of the results of Model – 2 in table 5, shows that there are many highly significant lags. I suggest that they are due to the extreme volatility of 2008. More uncertainty about the future and general financial turmoil, I assume, will increase the sensitivity to changes in the price of input factors, and lead to a (over) correction in the endogenous variable. An interesting feature of this model is that certified emission reductions show up as a good explanatory variable. I attribute this to changes in the European Union exchange traded scheme and the shift from the first to the second phase (second stage started 1.th January 2008). European allowances are represented by lagged variables. Therefore I reaffirm my conclusion that emissions in general are very important input factors in Nordic electricity production. However, the EU ETS is a complex system that still is in the early phase, and therefore deserves further study. A thorough analysis would be an excellent addition to this thesis.

Model – 3 analyzes observations from 2007, three years before delivery. Therefore I conclude that this model is a good representation of the market without interference of weather-driven variables. The German base load contract, coal and European allowances are represented by the contemporaneous observation which suggests that new information is taken into account immediately. The amount of significant lags has decreased, and resembles that of Model – 1. Uniquely to this model we can see that the static long run multiplier is interpretable (see table 10)

Model – 4 is, uses data sets from Models – 1 to 3, stacked. The concluding results from Model – 4 are that it is a good representation of the day to day changes in the structural parameters, similar to that of Model – 1 and 2. Based on this model, we can also confirm our initial hypothesis of the explanatory power of oil. We find that the price of oil is a statistically significant explanatory variable.

In Model – 3.1 (the fifth model) results of the re estimation of Model – 3 is presented. Here the German base load contract is endogenous in addition to the Nordic contract. We confirm a known issue when using OLS on simultaneous equation systems, which generally leads to a bias. My findings are that IV-estimation gives a higher estimated coefficient of the German base contract than we obtained by OLS. Hence the result for Model – 3 is robust to the choice of estimation method.

As a general comment I would suggest that my findings support the assumption that fuel prices in the forward market is a vital to understand the forward price of electricity. Although, the effect might not be as dominant as expected, and may only show up in lagged form. I also find that the explanatory power of variables vary from year to year, which suggest shifting importance over time. On the technical side, the use of a “strict” one present critical level might be part of the explanation, and we might very well return different results using “less strict” initial settings.

A natural expansion to this thesis would be to use Models – 1 to 3.1 as a starting point in forecasting of future prices. In addition a more in-depth and complex analysis of the emission market would be interesting, especially given todays focus on climate change and clean energy. The “weather variables” and renewable sources are also vital pieces of the puzzle, which for the sake of time had to be left out this time.

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### **From the World Wide Web**

Reference to the energy act of 1991 [<http://www.lovddata.no/all/nl-19900629-050.html>] taken 10.05.2012 09:00

Facts from our history [<http://www.nasdaqomxcommodities.com/about/ourhistory/>] taken 14.05.2012 10:00



Seasonal weather forecast [[http://met.no/Sesongvarsel%3A+mai-juli.b7C\\_w7LMYN.ips](http://met.no/Sesongvarsel%3A+mai-juli.b7C_w7LMYN.ips)]  
taken 08.03.2012 17:00

Uranium is not traded in an open market (Wikipedia1)  
[[http://en.wikipedia.org/wiki/Thermal\\_power\\_station](http://en.wikipedia.org/wiki/Thermal_power_station)] taken 10.05.2012 12:00

The European Union Emission Trading scheme (Wikipedia2)  
[[http://en.wikipedia.org/wiki/European\\_Union\\_Emissions\\_Trading\\_Scheme](http://en.wikipedia.org/wiki/European_Union_Emissions_Trading_Scheme)] taken  
02.02.2012 19:00

Ramsey RESET test [[http://en.wikipedia.org/wiki/Ramsey\\_reset\\_test](http://en.wikipedia.org/wiki/Ramsey_reset_test)] taken 09.04.2012  
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